SMALLHOLDER FARM HOUSEHOLD LABOR ALLOCATION AND IDIOSYNCRATIC SHOCKS IN SOUTHERN GHANA

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ABSTRACT

Most studies investigating the role of uncertainty in smallholder decision making have focused on either shocks or some notion of risk based on variability. When analyzing household production behavior, considering only yield variability ignores the potential effect of shocks on yield variability, and input allocation decisions. In this thesis, both shocks and yield risk are considered. We use a two-period expected utility model to analyze smallholder labor allocation sequentially. The data for this paper were obtained from a panel survey conducted in southern Ghana from 1996 to 1997. The approach used in this paper allows the incorporation of temporal uncertainty by introducing the concepts of ex ante and ex post yield risk which were briefly discussed by Sandmo (1970) and Holt *et al*. (1992). We find evidence of sequential dependence of labor decisions. Labor allocation in the planting period of the season helped explain labor allocation in the subsequent preharvest period of the season. Damage to stored crops in the planting period and negative health events experienced by the household during the second part of the previous season are important for ex post labor allocation. Household ex post labor allocation responds positively to ex post yield risk. Households shift labor to non-farm activities in response to ex post yield risk in order to smooth their incomes.

BIOGRAPHICAL SKETCH

Asare Twum-Barima was born in Kumasi, Ghana but spent the early part of his childhood in both Ghana and Nigeria. He earned his Bachelor of Science degree in Agriculture in 2005 from the Kwame Nkrumah University of Science and Technology (KNUST), Kumasi, Ghana. After his first degree, he was appointed as a teaching/research assistant at the Department of Agricultural Economics, KNUST from September 2005 to August 2006. In November 2006, he moved to the United States with the aim of pursuing graduate education in agricultural/applied economics. In 2008, he was admitted to Cornell University and expects to receive his Master of Science in Applied Economics and Management in January 2011.

This thesis is dedicated to my mum, Josephine Serwaa Odukale.

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CHAPTER 1

INTRODUCTION

Smallholder farm households in West Africa deal with uncertainty on two fronts: covariate and idiosyncratic risk. Covariate risk affects a whole community while idiosyncratic risk is peculiar to a particular household and does not significantly impact other households in the community.[1] Due to their diffuse temporal and spatial distribution, the incidence of idiosyncratic shocks typically does not attract attention from government and non-government organizations. Examples of idiosyncratic shocks include death of a household member, loss of employment, sickness, unexpected expenses, disease attack on crops, crop failure, and lower than expected sales receipts. In the absence of formal insurance or credit institutions, idiosyncratic shocks may have dire implications for smallholder households. Even though smallholder households may have strategies for managing risk, they remain vulnerable to poverty since the effectiveness of these strategies in insuring their assets against shocks is not known. In the case of smallholder farm households, their on-farm input allocation may be regarded as a reflection of their response to risk. This assertion is corroborated by past studies of consumption and production behavior of smallholder rural households, which have clearly established that most households respond to some form of risk (Behrman *et al.*, 1997; Fafchamps, 1993; Kochar, 1999; Rose, 1999; Udry and Duflo, 2004).

[1]In this paper, idiosyncratic risk includes the possibility of experiencing idiosyncratic shocks.

In most rural West African areas, the household head is the main income earner and in most cases has more than one occupation. Most on-farm input allocation decisions are made by the household head since he/she control the resources of the household. When a smallholder farm household experiences idiosyncratic shocks, it can lead to sub-optimal on-farm input allocation, resulting in low crop yields. These idiosyncratic shocks (both household-specific and plot-specific) can affect labor quality by diverting the attention of the household from critical crop production tasks during the season. In addition, certain types of idiosyncratic shocks can directly or indirectly affect caloric intake which in turn affects the productivity of labor (Behrman *et al*., 1997).

Consequently, with the recurrence of idiosyncratic shocks the household can repeatedly experience low yields which can culminate in the household decreasing acreage and in extreme cases discontinuing crop production. In areas where there are limited employment opportunities, the recurrence of idiosyncratic shocks can put households in a quandary; they experience low crop yields due to idiosyncratic shocks, however, they are unable to completely shift from crop production due to limited opportunities. In this situation, households that repeatedly experience negative events that impact their agricultural productivity are unable to completely shift from crop production to another activity. In the long run this can result in some smallholder households becoming trapped in poverty and unable to recover from idiosyncratic shocks. For example, in the event of insect attacks, households whose sources of income are non-farm employment and crop production cannot easily shift from crop production to other non-farm activities. Hence, households have to make a difficult choice between maintaining the status quo and concentrating on non-farm activities.

In the past, many policies have been designed to help rural households cope with shocks, however, these policies have largely focused on covariate shocks and can not effectively address the negative effects of idiosyncratic shocks. By gaining insight into smallholder on-farm input allocation behavior, both governmental and non-governmental institutions can design better policies to specifically deal with the effects of idiosyncratic shocks and their associated risks on smallholder farm households. This paper aims to investigate the impact of idiosyncratic risk and shocks on household labor decisions.

In a study of labor supply in rural India, Rose (2001) established that smallholder households respond to risk both ex ante and ex post. When smallholder households make ex ante on-farm input allocation decisions, they are made in anticipation of the occurrence of shocks in the future and their knowledge of risk based on available information. In this paper, this form of temporal risk is termed "ex ante risk." *Ex ante* risk[2] is based on the household's subjective distribution of the outcome of an activity. In crop production, the household knows the subjective yield distribution through observation of yields over time and/or across different households. This makes the second moment of the subjective distribution of yield a good candidate for representing the riskiness of crop production.

After the realization of stochastic events and other information relevant to the production process, the household updates its decisions by incorporating the new information into its decision-making process. In this thesis, the risk that is revealed to the household after the realization of shocks will be termed "ex post risk"[3] since the household cannot determine it until new information becomes available.

There have been numerous studies on agricultural decisions under uncertainty. These studies can be divided into groups based on approaches which include: (i) those

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[2] The concept of ex ante risk or variability is briefly mentioned by Sandmo (1970). Refer to section 2.5 of the literature review for a discussion of Sandmo's work.
[3] The concept of ex post risk or variability is briefly mentioned by Sandmo (1970). Refer to section 2.5 of the literature review for a discussion of Sandmo's work.

that incorporate some measure of risk and risk aversion into the analysis of economic behavior under uncertainty in a single-period model (e.g., Chavas and Holt, 1996; Love and Buccola, 1991; Saha *et al*., 1994); (ii) those that analyze agricultural decisions taking into the stochastic and dynamic nature of agricultural production (e.g.,, Behrman *et al.,* 1997; Fafchamps, 1993; Rose, 2000; Kochar, 1995, 1999; Skoufias, 1993); and (iii) those that analyze agricultural decision incorporating only the dynamic/sequential nature of agricultural production (e.g., Antle, 1983; Antle and Hathett, 1986).[4] The above categorization is far from exhaustive but it gives us an idea of some of the approaches that have been used for analyzing production behavior. This thesis contributes to the current literature by analyzing labor allocation taking into account both the incidence of shocks and the dynamic nature of agricultural production while incorporating a measure of risk faced by decision makers.

The kind of response employed by households in response to idiosyncratic shocks has implications for the distribution of household incomes and therefore long term implications for wealth accumulation. Due to the possible risk-increasing effects of poor timing of on-farm labor allocation, failure of the household to respond appropriately to idiosyncratic shocks can increase the riskiness (variance) of crop production and eventually result in them engaging in other income generating activities which are less risky but have a lower return.

One of the major decisions smallholder farm households make is on-farm labor allocation. During the season, households experience various types of shocks which include idiosyncratic shocks. As demonstrated by Fafchamps (1993) in his study of farmers in Burkina Faso, farmers respond to these shocks in their on-farm labor allocation. According to the study, farmers build flexibility into their farming practices which allows them to respond appropriately to shocks as they are revealed during the

[4] These and other similar studies are thoroughly discussed in Chapter 2.

course of the season. The subjective yield distribution of the household is then a function of their on-farm input allocation decisions in response to those shocks. Since shocks are exogenous, one of the practical strategies for controlling yield risk is on-farm input allocation before and after the realization of shocks.

There is strong empirical evidence in the applied risk analysis literature that most agricultural producers are risk averse. Saha *et al*. (1994) using farm-level wheat production data rejected the null hypothesis of risk neutrality in favor of risk aversion. Chavas and Holt (1996) in their study of corn-soybean acreage allocation decisions also confirmed the assumption of risk aversion among producers. In the context of risk aversion, the occurrence of idiosyncratic shocks can lead to attempts by the household to control risk using various risk management strategies. In the Akwapim South region of Ghana where the main source of livelihood is crop production, idiosyncratic shocks and risk elicit on-farm labor allocation behavior which can increase the riskiness of crop production due to increases in the variability of crop yield. This increase in variability can feed into households subjective yield distributions or perceptions of yield variability which has further implications for production efficiency and therefore farm income.

Smallholder farm households have many insurance strategies which include self-insurance in the form of liquid wealth. When households experience idiosyncratic shocks that impact their incomes, they employ one or a combination of strategies, including dissaving to smooth consumption, or reallocating their labor from farming to other activities.

In this thesis, I analyze smallholder household labor allocation *ex ante* and *ex post*. I focus on four issues. First, I explore the role played by self-insurance capacity (represented by wealth) of the household in their labor allocation. Does self-insurance capacity influence household labor allocation patterns? Assuming households are risk-averse, will poorer households allocate more labor to farming relative to their richer counterparts? Second, I analyze the ex ante and the ex post effects of risk and information on shocks on household labor allocation. What is the effect of the household's knowledge of yield risk on labor decisions before and after they experience idiosyncratic shocks in the first part of the season? Third, I examine the impact of idiosyncratic shocks on yield risk. What is the relationship between idiosyncratic shocks and yield risk? Finally, I explore whether smallholder household labor allocation behavior insures their yields against idiosyncratic shock by reducing exposure to yield risk.

The theoretical framework for this paper is a two-period expected utility model where households make ex ante labor allocation decisions in the first period and both ex ante and ex post decisions in the second period. Ex ante labor allocation decisions are made based on observed shocks, ex ante yield risk and any other relevant information. On the other hand, ex post labor allocation decisions are made using ex post yield risk and other available information as variables. I assume the household knows the stochastic crop production technology from experience. In this thesis, I use the Just-Pope method to estimate the conditional variance of crop yield. Analyzing labor sequentially will enable us to explore the effects of temporal risk on labor allocation decisions.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

There has been a considerable amount of research into economic behavior in risky environments over the past few decades. Most of these studies have focused on agricultural production behavior and the role of risk in contexts such as savings, consumption, and agricultural production. The nature of agricultural decision making lends itself to several methods of analyses as it is fraught with risk from numerous sources which influence decision making.

Most studies have analyzed agricultural production behavior in three ways: structurally estimating risk preference and production technology parameters; experimental, nonstructural, or structural estimation of only risk preference parameters; and analyzing agricultural production decisions using a reduced form approach. The structural approach involves making assumptions about the utility functional form while the reduced form approach sometimes involves assuming a risk preference structure. In another group of studies, a second dimension is added by analyzing economic behavior in a dynamic/sequential framework. The majority of empirical studies investigating farmer risk attitudes have been consistent in their findings: they reject risk neutrality in favor of a risk averse behavior. However, the situation has been different for the findings on risk preference structure where results have been inconsistent or assumptions about underlying risk preference structures have varied from one study to another.

The role of risk has also been studied extensively by incorporating some notion of risk or shocks into models (mostly dynamic) for analyzing production, consumption and savings decisions in rural areas of developing countries. The findings from these studies have been conclusive and provide substantial evidence of the importance of risk in agriculture except for very few cases (e.g., Smith and Umali, 1985). In the next sections, I review a number of studies analyzing the role of risk in agricultural production and decision making.

2.2 Stochastic Specification of Production Functions and Risk Considerations

Just and Pope (1978) proposed stochastic specification of production function which allows for a flexible relationship between output variance and inputs. This specification ensures independence between the variance and mean of output. In their study, they demonstrated that by using common production specifications where the stochastic component is incorporated either multiplicatively or additively, the effect of agricultural inputs on output variability is positive *a priori*. In their paper on production function estimation and related risk considerations, Just and Pope (1979) used the stochastic specification they proposed earlier to estimate input effects on the probability distribution of output. They showed that by using their proposed stochastic specification, we can obtain consistent and efficient estimators for the variance and mean of output. Using yield data collected from a controlled experiment, they found that fertilizer had a variance-increasing effect on yield; however, the estimated marginal variance contribution was much smaller than one obtained using standard log-linear disturbance approach which assumes homoscedasticity. Their results demonstrated that the stochastic specification eliminates most of the bias resulting from traditional production function, however, if the specification fails to take into account the direct effect of shocks on the deterministic and stochastic components of the production. The study also did not take into account the dynamic/sequential nature of the agricultural production which is important due to the timing of fertilizer application.

The Just-Pope variance estimator and its extensions have been used in other studies to examine the role of risk in agricultural. Kumbhakar and Tveterås (2003) using the Just-Pope framework derived a risk preference function under production risk and maximization of the expected utility of profit. They found evidence of heterogeneity among salmon farmers. Capital and labor were found to be risk-decreasing while feed and fish input were risk-increasing. Consistent with other studies, farmers in the sample used were found to be risk averse. In addition they exhibited downside risk aversion. By using a risk preference function flexible enough to test for the different risk preference structures (e.g., increasing, constant, and decreasing absolute risk aversion), no assumptions were made about farmers' risk behavior. In another study by Appelbaum and Ullah (1997), the demand and supply decisions of firms under uncertainty are analyzed in a framework which uses the principle of duality and non-parametric estimates of the first four moments of an unknown price distribution. They concluded that higher moment plays a significant role in determining input (demand) and output (supply) decisions. They rejected the null hypothesis of risk neutrality and concluded that producer response indicated risk aversion and are consistent with behavior under decreasing absolute risk aversion.

Holt and Moschini (1992) proposed an alternative measure of risk in commodity supply models. They investigated the role of price risk in sow farrowings using bivariate ARCH-M and GARCH-M models and a nonparametric kernel estimator. They accounted for the relevant time horizon of irreversible supply decisions, predictions for mean price and conditional variance were iterated forward. They used a theoretical framework which specifically assumed that producers had a constant absolute risk aversion (CARA) utility function and that price risk was conditionally normal. The concepts of ex ante mean and variance of price were briefly introduced. Their empirical results varied markedly in terms of their implication for risk response in hog supply decisions. The supply models estimated in a bivariate ARCH-M or GARCH-M framework suggested a small and negative risk effect on sow farrowing decisions and these were more plausible than those obtained using either a two-step parametric or non-parametric approach.

One of the commonest assumptions about the stochastic of conventional production function is tested in a study by Antle (1983). In the paper, a flexible representation of a firm's stochastic technology was developed based on the moments of the probability distribution of output. Large sample estimators were developed for a linear moment model that is sufficiently flexible to test the implicit restriction imposed by conventional production function specifications. Using milk production data, the first three moments of output were found to be statistically significant functions of inputs. Cross-moment restrictions were however rejected. This is consistent with the stochastic structure of the production functions specification proposed by Just and Pope (JP) (1979).

In a related study of the stochastic component of production functions, Griffiths and Anderson (1982) proposed two production function models with error components for time and firm and a heteroscedastic disturbance. The two production models were two specifications based on the JP framework. The issue of heteroscedasticity was addressed with a non-linear heteroscedastic error model. Both specifications permit the variance of output to increase or decrease as one of the inputs is increased. Applying these models to data from the pastoral zone of eastern

Australia, they found labor, water and possibly fencing, were likely to reduce the variance of wool production. They also found that sheep, buildings and land, were likely to increase variance. The variance decreasing attribute of labor and fencing—which may be considered as some form of capital—is consistent with the findings of other studies (e.g., Kumbhakar, 2002 and 2003).

2.3 Consistency and Efficiency of Parameter Estimates

In order to improve consistency and efficiency estimates there have been a number of studies where technology and risk preference parameters have been jointly estimated. In their paper, Saha *et al.* (1994) used the expo-power utility function which Saha (1993) had proposed in an earlier study to estimate the risk preference structure, degree of risk aversion and production technology of Kansas wheat farmers. In the 1993 study, Saha empirically demonstrated the ability of the expo-power utility function to exhibit decreasing, constant, or increasing absolute risk aversion and decreasing or increasing relative risk aversion, depending on parameter values. A Just-Pope specification of the production function was used for the analytical framework and also estimating the stochastic part of the production function. The study provided evidence which rejected risk neutrality and suggested decreasing absolute risk aversion (DARA) and increasing relative risk aversion (IRRA). Their results also showed that jointly estimated parameters were more efficient than separately estimated ones.

Using the joint estimation strategy, Chavas and Holt (1996) developed a method for estimating risk preferences and technology of corn-soybean farmers. Their approach was based on numerical methods nested within a Full Information Maximum

Likelihood (FIML) technique. This technique was used for estimating all the parameters of the production function and the first order conditions associated with the maximization of expected utility. Production and risk preference parameters were then recovered from results of the FIML estimation. The results of the study indicated that corn-soybean farmers were risk averse and exhibited DARA and downside risk.

Love and Buccola (LB) (1991) used a negative exponential utility function for representing risk preference and a Just-Pope specification of the Cobb-Douglas function for the technology of Iowa corn farmers. A negative exponential utility function implies CARA. By incorporating the two functional forms into a primal problem and solving for optimal input levels, they jointly estimated risk preference and technology parameters. Their estimates of risk aversion for different areas confirmed the common assumption that producers are risk averse. Surprisingly, some fertilizers (e.g., potassium) were found to be risk reducing. They therefore asserted that risk aversion and inputs' effects on yield risk combined to have significant implications for supply and input demand.

Commenting on the LB study, Shankar and Nelson (1999) argued that depending on the manner in which production residual is modeled "(in)consistency" is not an issue. They constructed their argument by using a Just-Pope production specification to demonstrate that irrespective of the specification of risk preferences, separate estimation of production will result in consistent estimates. On the contentious issue of efficiency, they conceded that joint estimation may be desirable from an efficiency standpoint; however, they pointed out that this comes at the price of imposing "severe restrictions" on the modeling of preferences and/or technology.

2.4 Stochastic and Dynamic Models for Analyzing Role of Risk

In another class of studies, the dynamic/sequential nature of agricultural production and decision making in risky agricultural environments have been addressed by using dynamic or multiperiod models. Risk aversion is normally incorporated into these models (using an expected utility framework) to take into account the risk attitudes of decision makers. Fafchamps (1993) used a finite horizon stochastic model of behavior to analyze labor decisions of small farmers in Burkina Faso, West Africa. The parameters of the model (utility and production) were structurally estimated using iterative FIML. The estimation focused on measuring flexibility in production and intertemporal substitutability in consumption. The paper (p. 1173) concluded low levels of agricultural labor efforts commonly observed were a consequence of low productivity of labor and of farmers' awareness that "in the absence of a labor market, overly ambitious production plans lead to seasonal manpower constraints." The utility functional form chosen implicitly assumed CARA risk preference structure. With emphasis on the temporal nature of risk, Krautkraemer, Kooten and Young (1992) distinguished between intra- and inter-year risks in a temporal problem. They compared empirical results from three alternative treatment of risk (risk neutrality, Katoaka's[5] and expected utility criterion) in a stochastic dynamic programming framework. In the case of the katoaka's and expected utility criterion, farmers' decisions are analyzed taking into account intra- and interyear risk aversion which raises issue about violation of the independence axiom. They (Krautkraemer *et al.*, 1992, p. 877) proceed to generalize "for most problems where risk and nonneutral risk preferences are clearly important, incorporating risk preferences (and violating or

[5] The Katoaka criterion is a safety-first criterion where the decision maker is assumed to be risk neutral with respect to interyear uncertainty but exhibit risk aversion with respect to intrayear uncertainty (Krautkraemer, Kooten and Young, 1992). The source of uncertainty is soil moisture level.

bypassing the independence axiom) will probably bias the results less than assuming false risk neutrality."

The seasonal labor utilization in agriculture among agrarian households in India was studied by Skoufias (1993) using a dynamic stochastic model of labor demand of farm households. Seasonality was modeled as a dynamic two stage process (planting and harvesting) with sequential dependence of decision. Risk aversion was incorporated into the theoretical model using a utility function to represent farmer risk preference. Panel data econometric methods were used to solve the problem of omitted variable bias due to farmer-specific heterogeneity. Yield risk was found to be an important determinant of behavior only in the planting stage. The paper suggested that ignoring the timing of application of labor inputs and/or heterogeneity arising from differences in risk preferences has a significant impact on estimated responses.

Under the assumption of risk averse behavior of farmers, Lamb (2003) developed a two-period model for analyzing fertilizer use, risk and off-farm labor market. The results suggested that off-farm labor and own-farm production may be complementary in risky production environments. The labor market was found as a means for the household to smooth income in the face of shocks to agricultural production.

2.5 Analyses of Decision Making in Risky Agricultural Environments

The response of rural household decisions to uncertainty has been studied in contexts such as storage, labor supply and savings. Many approaches have been used for analyzing the effect of risk on decision making. Other studies have treated this topic more theoretically (e.g., Sandmo, 1970).

Kochar (1999) studied the response of Indian farm households to idiosyncratic or household-specific income shocks using a dynamic model which divides the agricultural season into two stages. The model is used to analyze the effects of forecast or surprise in income on labor decisions. The paper explained that smoothness of household consumption in the presence of idiosyncratic income shocks reflected the ability of the household to smooth income directly, by increasing their market hours of work.

Rose (2001) studied the ex ante and ex post labor supply response of rural Indian farm households to risk. A panel data set spanning 13 states in rural India merged with a 22-year series of district-level rainfall data were used. It was found that ex ante, households facing riskier distribution of rainfall were more likely to participate in the labor market. Ex post, the experience of bad weather and low rainfall increased labor force participation. In this paper, panel regression methods were used to control for the effects of unobservable variables such as land quality. However, this correction does not completely remove omitted variable bias resulting from the experience of idiosyncratic shocks by households.

In a study of risk and savings by Udry (1995), the savings behavior of households in the presence of idiosyncratic adverse shocks in Northern Nigeria was examined using a reduced form approach. The results of the study suggested that household reduce their savings by large amounts in response to adverse shocks on their upland plots. They also suggested that consumption smoothing is effected through adjustments in savings in assets not subject to diminishing returns. The data used for this study were panel in nature and these were used to control for time-invariant unobservables using fixed effect regression.

The savings behavior of rural Pakistan households has also been analyzed using dynamic models. Behrman *et al.* (1997) using a stochastic dynamic multistage agricultural household model examined the relative importance of alternative forms of savings in the presence and absence of formal financial intermediaries. They provided evidence that the presence of financial intermediaries importantly influences the use of formal saving and transfer for income smoothing. The evidence of income smoothing is consistent with the results of other studies. They also found significant biases in the evaluation of savings-income relationships that are inattentive to within-year dynamics of agricultural production. The theoretical framework for the study only considered production shock and failed to incorporate the possibility of forward-looking behavior which have been found in other studies.

In a theoretical study, Sandmo (1970) used a two-period model of consumption and investment to analyze the effect of uncertainty on savings decisions. Two types of uncertainty were considered: income and capital risk. By assuming risk aversion and that ex post variability goes together with ex ante uncertainty, it was concluded that there is a significant difference in the savings behavior between wage and salary earners, and self-employed persons. The paper argued that farmers and businessmen have more variable incomes than the self-employed.

The role of information in economic decision making has also been investigated in a number of studies. Chavas *et al.* (1991) investigated the role of temporal uncertainty and information issues in economic decisions. Using a two-period model where the decision maker is assumed to be an economic agent facing a two-period planning horizon and a preference function in a dynamic programming framework. They showed that the nature of the economic environment can influence the valuation of information, which in turn affects choice functions considered in the study.

Saha and Stroud (1994) analyzed on-farm grain storage decisions of farmers facing price risk using a model of inventory demand. They further assumed that the farm household maximizes a time-wise additively separable and time-invariant utility function over a time horizon of T periods. Their empirical results provided evidence against risk-neutral preferences. They also found that risk response was particularly significant for storage and labor decisions of small farmers.

Smith and Umali (1985) demonstrated that low levels of fertilizer use on rainfed rice in the Philippines could not be attributed to production risk. They used a random coefficients model to estimate the objective distribution of yield. They then incorporated it into a utility-maximization framework to predict the behavior of rice farmers in the Philippines. According to these predictions, moderately risk averse farmers apply seven to ten kilograms less than the profit-maximizing nitrogen-rate. They claimed that their results were consistent with other studies that found that risk was not a major impediment to fertilizer use in irrigated areas.

2.6 Production Efficiency and the Effect of Shocks

The sources of production inefficiencies have been explored by taking into account the possible role of both idiosyncratic and covariate shocks. Some studies have directly or indirectly tested the hypothesis that shocks affect input productivity. Other studies have considered the caloric effect of consumption on productivity.

Larson and Plessmann (2009) used a detailed panel of household and production data and time series of temperature and rainfall data to explore why farmers often fail to achieve efficient production outcomes. The study focuses on rice production among farmers in the Bicol region of the Philippines. The household problem is stated as a time-separable lifetime consumption planning problem. They found evidence that diversification and input choices affect efficiency outcomes among farmers, although the effects are not dominant. Efficiency outcomes were also determined by accumulated wealth, past decisions to invest, favorable market conditions and weather.

In another study of productive efficiency among West African rice farmers, Barrett *et al.* (2006) using a standard household model that maximizes utility subject to budget, time availability and technology constraints, explained how macroeconomic shocks might temporarily divert managerial attention. They found a transitory increase in mean plot-level technical inefficiency among Ivorian rice producers and considerable variation in the magnitude and persistence of this effect. The effect was attributable largely to ex ante complexity of operations, and the educational attainment and off-farm employment status of plot managers.

The impact of caloric consumption on production efficiency has been investigated among farm households in rural areas. Behrman *et al.* (1997) taking advantage of panel data on farm households from rural Pakistan, estimated the calorie response to the different components of income which included agricultural production. Similar to their study of savings decisions, they employed a stochastic dynamic multi-stage household model which assumes that households maximize expected discounted utility for analyzing consumption decisions and their productivity effects. Their estimates for calorie response indicated that the income-calorie relationship depended importantly on the production stage, form of income, liquidity of assets and the extent to which income is anticipated. Income shocks were found to have a significant positive effect on consumption during the harvest stage.

Some studies have jointly estimated risk, risk preferences and technical efficiency, an example of such a study is Kumbhakar (2002). In this paper, risk preferences and technical efficiency were estimated using two specifications: an additive model and a multiplicative model. In the additive model, the efficiency term was introduced additively into the JP model. In the case of the multiplicative model, technical efficiency was introduced in a multiplicative form. No assumptions were made about the parametric form of the utility function and the distribution of the error term representing production risk. A sample of Norwegian salmon farms was used to illustrate the workings of the model. The study found that all farmers were risk averse. Evidence was presented to the effect that production risk increased with feed and decreased with labor and capital. Consequently, technical inefficiency was found to be positively related to feed and negatively related to labor and capital. This finding is consistent with other studies.

2.7 Dynamic Agricultural Production Models and Input Decisions

There is considerable literature on production function analysis which has incorporated the dynamic/sequential nature of agricultural production. Some of these studies have proposed econometric methodologies for analyzing dynamic production processes in agriculture. These methodologies address the problem arising from intermediate inputs: intermediate input decisions may be endogenous to final output and intermediate inputs are likely to be correlated with each other and other variables, making identification and estimation difficult. These methodologies have been extended to other studies by incorporating risk into them.

In the study of sequential decision making in production models, Antle (1983a) formulated a short-run single-product production model with a stochastic control framework and explored its implications for specifying and estimating econometric production models. The analysis in this paper demonstrated that sequential solutions generally result in input demand equations which differ from those of one-period solutions. The paper also demonstrated that depending on assumptions about information used and data availability, sequential solutions may produce models which require either single-equation or simultaneous-equation estimation methods. Using four different information sets, four types of solutions to the problem were obtained: open loop control, sequential updating, open loop with feedback and close loop solution. The framework for analysis was a two-period Cobb-Douglas model.

Antle and Hatchett (1986) in their study developed an econometric methodology for estimating dynamic models with sequential intermediate input decisions. A Cobb-Douglas specification was used to represent the production function. They viewed crop production as a dynamic optimization problem, with input decisions made sequentially in response to the state of the production system. The dynamic optimization problem was solved to obtain a system of demand equation which was estimated econometrically using four different approaches: static single-stage, static three-stage, dynamic linear system and dynamic non-linear system. The estimates of the dynamic models were found to be consistent and more efficient than the static models. Even though the Cobb-Douglas specification was restrictive and implicitly imposed many assumptions about the stochastic structure of the system, the study provided a basis for analyzing production risk and its role in decision making. The study ignored unexplained differences across farms; however, this was addressed by using wheat production data obtained from six large farms in the Imperial Valley of California for the harvest seasons 1980 to 1983.

Agricultural production processes have been modeled in the context of livestock production. Chavas *et al.* (1985) in their study modeled a crop and livestock production process. They explained that crop and livestock production processes are typically dynamic and involve growing biological assets. A production model of biological growth based on a differential equation specification was used.

They suggested that knowledge of biological growth needs to be incorporated into the study of economic efficiency of production processes of a biological nature since biological processes are dynamic in nature.

In a paper discussing the importance of incorporating risk in production analysis, Antle (1983b) used a dynamic and static model and a risk-efficiency hypothesis to analyze the role of risk in agricultural decision making. The risk-efficiency hypothesis states that risks affect both productivity and optimal resource used and, hence, economic and technical efficiency. The paper concluded that incorporating risk in production analysis means incorporating probability distribution parameters in decision models. It also concluded that static models have serious limitations in that risk matters only if decision makers are risk averse, and they cannot be used to model cost uncertainty. On the other hand, dynamic models support the risk-efficiency hypothesis and risk matters whether or not the decision maker is risk averse.

2.8 Econometric and Experimental Risk Estimation

The impact of risk on agricultural decision making has been investigated by jointly or separately estimating risk preference and technology parameters, these parameters are then used to make inferences about decision making. Risk preference has also been estimated by joint estimation of the structure of technology and input decision rules. Other studies have investigated the role risk plays in decision making by estimating risk preference using nonstructural econometric or experimental methods.

Antle (1989) estimated risk attitudes using a nonstructural approach. This approach did not require joint estimation of the firm's technology and input decision rules. A nonstructural approach replaced optimal input choice with the assumption that farmers optimally manage their portfolios of productive activities. It also utilized changes in patterns of net returns distributions over time to estimate the parameters of the distribution of risk attitudes in the population. Risk attitudes were estimated in three Indian villages and the results were compared to previous experimental and econometric estimates from the same villages. One advantage of the nonstructural approach is that it requires fewer modeling assumptions than the structural approach. Furthermore, it requires less information; however, it provides the researcher with only the estimates of risk attitudes as compared to the structural approach which provides estimates of the technology and decision rules as well.

Risk attitudes have been estimated in other studies using the experimental approach. Binswanger (1980) measured the risk attitudes of 240 households using two methods: an interview method eliciting certainty equivalents and an experimental gambling approach with real payoffs which, at their maximum, exceeded monthly income for unskilled laborers. The author conceded that the interviews were subject to interview bias and results were totally inconsistent with the experimental measures of risk aversion. The study concluded that at high payoff levels, virtually all individuals are moderately risk averse with little variation according to personal characteristics. Wealth was found to reduce risk aversion slightly, but its effect was not statistically significant.

In a similar study also measuring risk attitude, Dillon and Scandizzo (1978) used experiments involving choice between risky and sure farm alternatives to assess the risk attitudes of samples of small farm owners and sharecroppers in Brazil. Their results indicated most subsistence farmers were risk averse, and risk aversion tended to be more common and perhaps greater among owners than sharecroppers. Estimation of risk attitude coefficients was based on mean-standard deviation, mean-variance, and exponential utility functions. They concluded in an expected utility context, distribution of risk attitude coefficients was diverse and not necessarily well represented by an average sample value. They also found that the level of income and other socioeconomic variables influence peasants' attitudes towards risk.

Using an econometric approach, Moscardi *et al.* (1977) derived the risk attitudes of peasants in Puebla, Mexico, from survey data using a model of safety-first behavior. Measurements of behavior toward risk were explained by a set of socioeconomic and structural variables that characterize peasant households. They proposed that knowledge of the determinants of attitudes toward risk is useful for the purpose of tailoring technological recommendations to particular categories of peasants. Based on the results of the study, they concluded that risk aversion is responsible for substantial differences between the demand for fertilizer without risk and actual demand with risk. This conclusion was also supported by high estimated risk premiums discouraging the use of high rates of fertilizer under safety-first behavior.

The results of the above and other studies have been widely used for estimating the risk attitudes of decision makers. However, extrapolating the results of these studies for the purpose of understanding decision making in the presence risk without taking into account the differences in technology, constraints and other factors can lead to misleading conclusions about role of risk in agriculture.

2.9 Conclusion

The studies reviewed in the previous sections which involved the estimation or elicitation of risk preferences have generally confirmed the assumption of risk averse behavior among decision makers in rural areas of developing countries. For studies involving the estimation of risk attitudes, the distribution of the coefficients of risk aversion has varied. One possible explanation for this variation is the differences in the characteristics and environments of subjects in the sample used for the estimation. Another possible source of these differences is variation in methodology or approach employed in these studies. Therefore, in order to be able to accurately predict the behavior of decision makers, it is important to consider the environment or settings in which they make decisions.

There have also been inconsistencies in direct or implicit assumptions about risk preference structures used in a number of risk studies. Some studies have tested directly for risk preference structure and the results have been mixed. Saha (1993) found evidence of DARA and IRRA while Chavas and Holt (1996) found a CARA risk preference structure. Love and Buccola (1991) implicitly assumed CARA using an exponential utility function for representing risk preference. These inconsistencies have been resolved in some studies by using flexible functional forms which do not impose any restrictions of the risk preference structure. However, this approach normally has high data requirements due to the problem of increased parameter identification demands.

Other risk studies have focused on investigating the influence of agricultural inputs on the variance of output. There seems to be a consensus about the negative influence of labor and capital on output risk (e.g., Griffiths and Anderson, 1982; Kumbhakar, 2002; Kumbhakar and Tveterås, 2003). Fertilizer has been found to have a positive influence on the variance of output; however, Love and Buccola (1991) found that potassium has a negative effect on variance. In a study of the effect of fertilizer on risk, Rosegrant and Roumasset (1985), using a heteroscedastic production function with measurable stochastic inputs, found that estimating optimal inputs without environment-specific information about the sources of risk leads to large errors. They also suggested that moderate risk aversion can account for 6.7 to 16.7 percent reduction in nitrogen use (relative to the risk-neutral solution) for selected rice producing area of the Philippines. This shows that it may be possible that nitrogen has a positive effect on risk in some environments. The implication of these findings is that it is important to consider type or content of fertilizer when studying the effect of inputs on risk. They asserted that the influence of measurable stochastic inputs on risk underscores the value of collecting information about the sources of risk and of exercising caution when information is not available.

On the issue of consistency and efficiency of parameters of technology and risk preference, some authors have proposed the joint estimation of risk and technology structure of decision makers (Chavas and Holt, 1991; Love and Buccola, 1991; Saha *et al.*, 1994) is important if the research is interested in obtaining consistent and efficient estimates. However, Shankar and Nelson (1999) argued that depending on the manner in which production residual is modeled "(in)consistency" is not an issue. They constructed their argument by using a Just-Pope production to demonstrate that irrespective of the specification of risk preferences, separate estimation of production will result in consistent estimates. Although the econometric issues of consistency and efficiency are far from resolved, the use of flexible functional forms for modeling production and variance seem to be very promising based on the empirical demonstration of their ability to at least consistently estimate parameters of risk preference and technology.

In this thesis, I examine the role of idiosyncratic shocks in smallholder labor allocation in Ghana. I assume that similar to covariate shocks (Barrett *et al.*, 2006), idiosyncratic shocks are a possible source of production or yield risk in rural areas of developing countries. I incorporate the concept of ex ante and ex post risk (variance) articulated by Sandmo (1970) and mentioned briefly by Holt and Moschini (1992) in their study into a two-period expected utility model where households make ex ante labor allocation decisions in the first period and ex post decisions in the second period. Using this framework and a panel data set, I analyze the impact of idiosyncratic shocks on labor decisions, productivity and yield risk.

CHAPTER 3

THEORETICAL FRAMEWORK

3.1 Two-Period Household Labor Allocation Model

The farm inputs to be considered in the analysis of on-farm input allocation are labor and land.[6] The theoretical framework for this thesis is based on a two-period utility model. I assume that household preferences are represented by a von Neumann-Morgenstern utility function $U(\cdot)$ which is twice differentiable. In addition, the utility function satisfies, $U'(\cdot) > 0$ and $U''(\cdot) < 0$, indicating local non-satiation and risk aversion, respectively. I further assume the household has a yield function represented by $f(\cdot)$ which they know through experience and observation of neighbors and has the following properties: $f(\cdot) \geq 0$, $f'(\cdot) > 0$ and $f''(\cdot) < 0$. Households are assumed to allocate on-farm labor to maximize expected utility of terminal wealth subject to their crop production technology and labor constraints. The assumption that households have labor constraints might not necessarily be the case. In this thesis, this is not tested due to lack of data on household labor availability by round. The households are assumed to supply all their on-farm labor since most households in Akwapim South rely on their own labor for crop production. I assume that crop production does not involve any costs. There are virtually no purchased inputs in this system and the valuation of on-farm labor is a complicated exercise which is beyond the scope of this thesis.

This thesis focuses on the ex ante and ex post effects of risk on household on-farm labor allocation. The household production decision process is made amenable to

[6] Chemicals are dropped from the analysis because only a few households used them.

a stochastic dynamic household model by dividing the household production decision process into two periods based on the crop production cycle of maize. In the first period, on-farm labor allocation decisions are made based on factors which include ex ante yield risk, shocks realized (from previous period) and expected future shocks. Shocks are realized by the start of the second period. Ex ante yield risk is represented by conditional yield variance in the planting period. Since the household does not know how much on-farm labor they will allocate in the preharvest period, they form expectations about on-farm labor which they use to determine the conditional yield variance they will face. The household incorporates this new information into their labor allocation decisions and hence updates its subjective yield risk perception.[7]

The first period is termed "planting period" and the second period "pre-harvest period." The planting period is the period from planting until crop establishment. The pre-harvest period is the period after crop establishment until maturity. Harvest period labor is excluded from the analysis in this thesis due to the proportionality between yield and harvest period labor (Fafchamps, 1993).

To solve the household decision problem, I employ assumptions similar to those used by Antle (1983) for finding open loop solutions in the sequential crop production model.[8] The problem can be expressed as:

$$(1) \qquad \underset{l_{f1}, l_{w1}}{Max}\, E \ \underset{l_{f2}, l_{w2}}{Max}\, U\left(W_2\right)$$

[7] I use the term *ex post* yield risk to refer to the updated yield risk in the pre-harvest period of the season.

[8] The open loop control solution found by Antle (1983) uses the sequential dependence property assumption. This states that decisions made earlier may affect those made later. This is similar to backward induction.

$s.t.$

The stochastic laws of motion for wealth

(2) $$W_1 = W_0 - C_1 + p_w A l_{w1} + I_1$$

(3) $$W_2 = W_1 + p_y A y_2 - C_2 + p_w A l_{w2} + I_2$$

The Just-Pope stochastic yield function for the household

(4) $$y_2 = f(l_{f1}, l_{f2}, s_0, s_1) + h^{\frac{1}{2}}(l_{f1}, l_{f2}, s_0, s_1)\varepsilon$$

The household labor constraint

(5) $$l_{fp} + l_{wp} = L_p \qquad \text{where } p = 1,2$$

where W_0, W_1 and W_2 denotes the initial, intermediate and terminal period wealth of the household, respectively; y_2 denotes maize yield (output per acre) during the harvest period of the cropping season at the end of period 2; p_y is the output price per kg for maize; l_{wp} is the household non-farm labor allocated per acre in period *p*; p_w the market wage rate; A is the predetermined area before the beginning of the season; l_{fp} is household labor allocated to crop production per acre in period *p*; L_p denotes household labor availability per acre in period p; s_p denotes idiosyncratic shocks experienced by the household in period p, and I_p denotes exogenous income earned by the household from crops other than maize and non-farm activities in period p. C_p is household subsistence (exogenous) consumption requirement in period p; ε is the stochastic disturbance term with zero mean and constant variance.

Household- and plot-specific idiosyncratic shocks are incorporated into the household crop production technology based on the assumption that the total amount of effective on-farm work done is a function of idiosyncratic shocks experienced by the household.[9] Effective on-farm labor allocation is represented as:

$$l^e_{f1} = l^e_{f1}\left(l_{f1}, s_0\right) \qquad\qquad l^e_{f2} = l^e_{f2}\left(l_{f2}, s_0, s_1\right)$$

Therefore information on idiosyncratic shocks is assumed to affect the productivity of labor allocated by the household.

Using backward induction, I first consider the household decision problem in the second period. The household allocates labor to maximize the utility of terminal wealth subject to their crop production technology and labor constraints.

(6) $$U\left(W_2^*\right) = \underset{l_{f2}, l_{w2}}{Max} U\left(W_2\right)$$

$s.t.$

(7) $$W_2 = W_0 - C_1 + p_w A l_{w1} + I_1 + p_y A y_2 - C_2 + p_w A l_{w2} + I_2$$

(8) $$y_2 = f\left(l_{f1}, l_{f2}, s_0, s_1\right) + h^{\frac{1}{2}}\left(l_{f1}, l_{f2}, s_0, s_1\right)\varepsilon$$

(9) $$l_{f2} + l_{w2} = L_2$$

The above problem can be expressed as the lagrangean α_2 below:

(10) $$\alpha_2 \equiv U\left(W_2\right) - \lambda_1\left(l_{f2} + l_{w2} - L_2\right)$$

Taking a partial derivative with respect to l_{f2}, l_{w2} and the lagrangean multiplier, λ_1, the first order conditions are:

(11) $$\frac{\partial \alpha_2}{\partial l_{f2}} = U_{lf2}\left(W_2\right) p_y A\left(f_{lf2}(\cdot) + \frac{1}{2} h^{-\frac{1}{2}}(\cdot) h_{lf2}(.)\varepsilon \right) - \lambda_1 = 0$$

(12) $$\frac{\partial \alpha_2}{\partial l_{w2}} = U_{lw2}\left(W_2\right) p_w - \lambda_1 = 0$$

$$l_{f2} + l_{w2} = L_2$$

[9] This is based on Behrman *et al*. (1997), where in order to allow for the possibility that calories influence productivity total amount of effective work is distinguished from the number of days contributed by workers.

Solving the above set of first order conditions simultaneously, I obtain the optimal allocation rules $l_{f2}^{*}(\cdot)$, and $l_{w2}^{*}(\cdot)$ for the preharvest period. The first order conditions can alternatively be expressed as:

$$(13) \qquad \frac{\partial U(W_2)/\partial l_{f2}}{\partial U(W_2)/\partial l_{w2}} = \frac{U_{lf2}(W_2)A\left(f_{lf2}(\cdot)+\frac{1}{2}h^{-\frac{1}{2}}(\cdot)h_{lf2}(.)\varepsilon\right)}{U_{lw2}(W_2)} = \frac{p_w}{p_y}$$

$$OR \qquad p_y U_{lf2}(W_2)A\left(f_{lf2}(\cdot)+\frac{1}{2}h^{-\frac{1}{2}}(\cdot)h_{lf2}(.)\varepsilon\right) = p_w U_{lw2}(W_2)$$

The household uses the output price and the market wage rate as weights for valuing the marginal utility it derives from crop production and participating in the labor market. In the preharvest period, labor is allocated between crop production and other income generating activities such that the marginal utility derived from both activities are equal.

In the planting period of the cropping season, the household allocates on-farm inputs to maximize the expected utility of terminal wealth subject to their crop production technology and labor constraints. I assume that the household knows and uses the optimal allocation rule $l_{f2}^{*}(\cdot)$, and $l_{w2}^{*}(\cdot)$ in the preharvest period. This assumption is similar to the “sequential dependence of decisions feature of sequential solutions” proposed by Antle (1983) and the idea of backward induction. Therefore using the decision rules for optimal on-farm input allocation, for the first period we solve:

$$(14) \qquad \underset{l_{f1},l_{w1}}{Max}\, EU\left(W_2^{*}\right)$$

$s.t.$

$$(15) \qquad W_2^{*} = W_0 + p_y A y_2 - C_1 - C_2 + p_w A\left(l_{w1} + l_{w2}^{*}\right) + I_1 + I_2$$

$$(16) \qquad y = f\left(l_{f1}, l_{f2}^{*}(\cdot), s_0, s_1\right) + h^{\frac{1}{2}}\left(l_{f1}, l_{f2}^{*}(\cdot), s_0, s_1\right)\varepsilon$$

$$(17) \qquad l_{f1} + l_{w1} = L_1$$

The lagrangean α_1 form of the problem is:

(18) $$\alpha_1 \equiv EU\left(W_2^*\right) - \mu_1\left(l_{f1} + l_{w1} - L_1\right)$$

Taking derivatives with respect to l_{f1}, l_{w1} and the lagrangean multiplier, μ_1, the first order conditions are:

(19) $$\frac{\partial \alpha_1}{\partial l_{f1}} = p_y E\left\{U_{lf1}\left(W_2^*\right)\left[f_{lf1}(.) + \frac{1}{2}h^{-\frac{1}{2}}(.)h_{lf1}(.)\varepsilon\right]\right\} - \mu_1 = 0$$

(20) $$\frac{\partial \alpha_1}{\partial l_{w1}} = p_w E\left\{U_{lw1}\left(W_2^*\right)\right\} - \mu_1 = 0$$

$$l_{f1} + l_{w1} = L_1$$

Equations (17), (19), and (20) can be solved simultaneously to get household optimal allocation decision rules $l_{f1}^*(\cdot)$, and $l_{w1}^*(\cdot)$ in the planting period. Similar to (13) the first order condition for the planting period can be written as:

(21) $$\frac{\partial EU\left(W_2^*\right)/\partial l_{f2}}{\partial EU\left(W_2^*\right)/\partial l_{w2}} = \frac{E\left\{U_{lf1}\left(W_2^*\right)A\left[f_{lf1}(.) + \frac{1}{2}h^{-\frac{1}{2}}(.)h_{lf1}(.)\varepsilon\right]\right\}}{E\left\{U_{lw1}\left(W_2^*\right)\right\}} = \frac{p_w}{p_y}$$

OR $$p_y E\left\{U_{lf1}\left(W_2^*\right)A\left[f_{lf1}(.) + \frac{1}{2}h^{-\frac{1}{2}}(.)h_{lf1}(.)\varepsilon\right]\right\} = p_w E\left\{U_{lw1}\left(W_2^*\right)\right\}$$

In the planting period, the household allocates labor subject to its labor constrain such that the expected marginal utility from crop production is equal to the expected marginal utility from participating in the labor market. The market wage rate and output price are used for valuing the marginal utilities for wage income and crop production, respectively. The household adopts a flexible approach in their labor allocation. They make labor allocation decisions based on available information and update their knowledge as temporal yield uncertainty is gradually resolved.

From the above, I obtain a system of equations consisting of optimal decision rules for each period which constitute the optimal on-farm input policy of the household. The reduced form of the solutions can be written as:

(22) $l_{w2}^{*} = l_{w2}\left(W_0, A, p_y, p_w, l_{f1}, l_{w1}, s_0, s_1, I_1, C_1, I_2, C_2, L_2, \sigma_2^2\right)$

(23) $l_{f2}^{*} = l_{f2}\left(W_0, A, p_y, p_w, l_{f1}, l_{w1}, s_0, s_1, I_1, C_1, I_2, C_2, L_2, \sigma_2^2\right)$

(24) $l_{f1}^{*} = l_{f1}\left(W_0, p_y, p_w, A, s_0, C_1, \overline{C}_2, I_1, \bar{I}_2, L_1, \overline{L}_2, \sigma_1^2\right)$

(25) $l_{w1}^{*} = l_{w1}\left(W_0, p_y, p_w, A, s_0, C_1, \overline{C}_2, I_1, \bar{I}_2, L_1, \overline{L}_2, \sigma_1^2\right)$

where $\bar{x}$ refers to mean of x and σ_p^2 denotes the conditional variance of wealth in period p.

Since most farmers are risk averse, an increase in yield risk is expected to negatively affect on-farm labor allocation in the planting and preharvest period as farmers opt instead for safer non-farm employment income. Therefore, non-farm labor allocations for the planting and preharvest periods are positively related to yield risk. They use this strategy to smooth their incomes and thereby reduce the variance of terminal wealth (W_2). The nature of crop production makes it riskier than labor market participation.

The decision rules for preharvest labor allocations depend on the functional forms for $f(\cdot)$ and thus on $\frac{\partial l_{w2}^{*}}{\partial l_{w1}^{*}}$ and $\frac{\partial l_{f2}^{*}}{\partial l_{f1}^{*}}$, which represent the marginal rates of substitution of preharvest labor for planting period labor in each sector. The relationship between initial wealth and labor allocation $\frac{\partial l_{f2}^{*}}{\partial W_0}, \frac{\partial l_{f1}^{*}}{\partial W_0}, \frac{\partial l_{w2}^{*}}{\partial W_0}$ and $\frac{\partial l_{w1}^{*}}{\partial W_0}$ are also ambiguous.

Idiosyncratic shocks such as health shocks can decrease the quality and quantity of labor available and therefore are expected to have a negative effect on crop yields. We would expect this to adversely affect labor allocation to crop production and potentially to non-farm employment as well.

CHAPTER 4

SURVEY REGION AND DATA

4.1 Data Collection

Data for this study were obtained from panel surveys conducted in 1997/98 among smallholder farm households in the Akwapim South district of southern Ghana. The survey was run from November 1996 to August 1998.[10] Questionnaires were administrated to 213 households out of 240 initially sampled. A total of 436 individuals were surveyed over the 15 rounds (Table 4.1 and 4.2).[11] The average period between rounds was about 2 months. The sample was constructed in two stages: purposive selection of villages in four clusters near Nsawam and Aburi, and then a random selection of 60 households from each cluster from the first stage (Udry and Goldstein, 1998). The villages are: Oboadaka, Pokrom, Konkonuru and Darmang-Ahweriase. Oboadaka, Darmang-Ahweriase and Pokrom are near Nsawam while Konkonuru is near Aburi. Nsawam is the district capital of Akwapim South, about 40km north of Accra, the capital of Ghana. Due to its proximity to the capital, it serves as a commercial centre for nearby villages. Aburi is also near the capital, about 45 minutes drive. Data were collected on variables such as household assets, output sales, quantity of harvest, plot activities, lending, borrowing, non-farm income, family expenses, and shocks experienced by the household.

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[10] The survey was conducted by Christopher Udry of the Department of Economics, Yale University and Markus Goldstein of the Department of Agricultural and Resource Economics, University of California, Berkeley. The data can be found at http://www.econ.yale.edu/~cru2//ghanadata.html

[11] Rounds refer to a data collection period during which questionnaires are administered to respondents. Therefore for this panel survey, respondents were surveyed a total of 15 times from November 1996 to August 1998. Variables for which data are collected are described in section A.2 of Appendix A.

Table 4.1—Number of Participants in Survey by Village

Survey Period	Participants	Konkonuru	Oboadaka	Pokrom	Darmang	Total
	Households	54	51	57	51	213
Nov 96-Aug 98	Individuals	112	102	111	106	429

In this thesis, I focus on smallholder farm households who cultivated maize and reported/experienced idiosyncratic shocks between the period November 1996 and August 1998. Based on these criteria, a total of 125 households were selected. The total number of plots owned by these households was 238, which imply most households cultivated maize on more than one plot. The selection process resulted in an unbalanced panel data set with multiple cropping seasons for all households and multiple plots in multiple seasons for most.

Table 4.2—Number of Households/Plots selected for Study by Village

Observational Units	Konkonuru	Oboadaka	Pokrom	Darmang	Total
Number of Households	29	44	13	39	125
Number of Plots	49	99	16	74	238

4.2 Smallholder Crop Production in Akwapim South

The four villages selected for this study are all located in the deciduous forest agro-ecological zones (Figure 4.1). Average annual rainfall in this region is 1500mm with major (beginning in March) and minor (beginning in September) rainy seasons (Morris *et al*., 1999). The length of the growing seasons in the major and minor seasons is 150-160 and 90 days, respectively (AQUASTAT Survey, 2005; Morris *et al*., 1999). The major food crops grown in this area are maize, plantain, cassava and other roots (Table 4.3). Crop production in this region, similar to most parts of Ghana, is rainfed thereby increasing the riskiness of production.

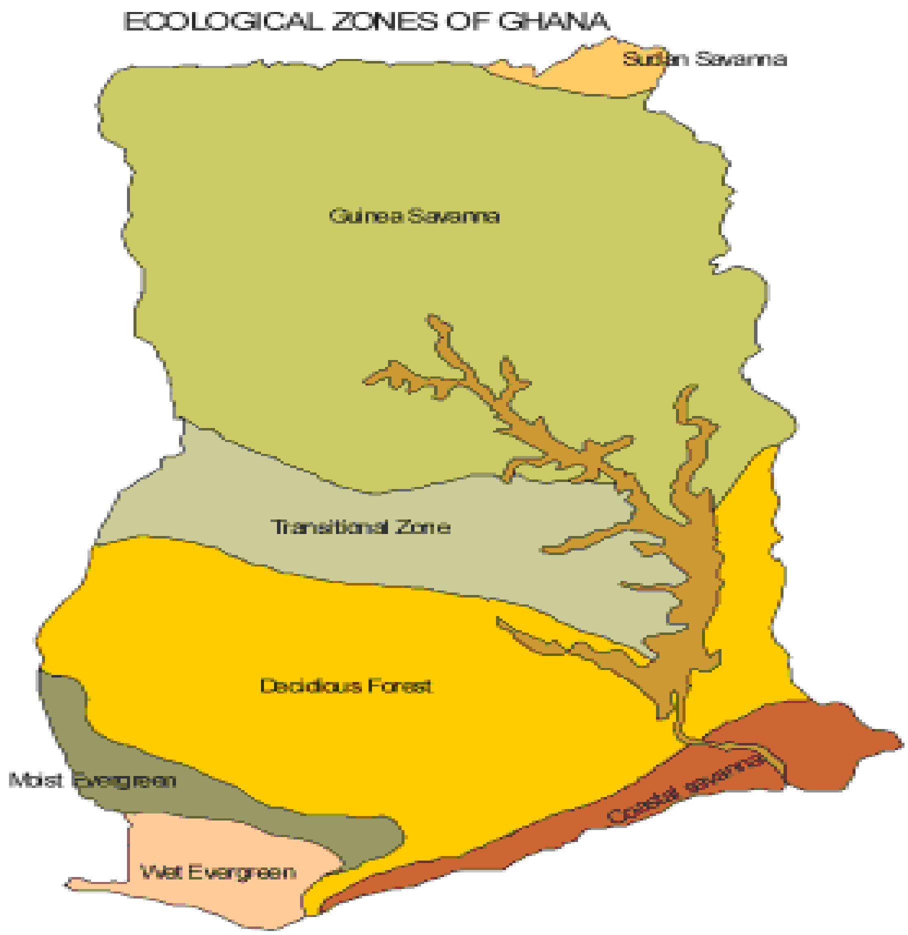

Figure 4.1—Agro-ecological Zones in Ghana

Source: http://www.fao.org/ag/aGL/swlwpnr/reports/y_sf/z_gh/gh_map/ghmp2301.gif

In addition to the crops above, smallholder households in Akwapim South cultivate a variety of cash crops including oranges, palm oil, pineapple, pepper, garden eggs, okra, and other vegetables. Most smallholder farm households engage in crop production primarily for subsistence. This coupled with diversification partly explains why these household cultivate multiple crops. For most smallholder farm households, land is not a constraint since they can easily rent land under various arrangements if they do not own land. Cassava and maize are the two most widely cultivated crops in Akwapim South (Table 4.3). Maize has a long shelf life and therefore can be stored for long periods of time and sold on the market when prices increase. Cassava on the other hand, does not have a long shelf life; however, it can be left in the field for long periods and harvested when needed.

In this thesis, I analyze on-farm input allocation behavior in the context of maize production. I focus on maize production for two reasons. First, maize is biannual and therefore we can analyze production decisions using short panel data that impede analysis of pineapple and cassava which are perennials with much longer periods of maturity. Certain improved varieties of maize have maturity periods as short as 90 days. Second, maize is the second most widely cultivated crop in terms of acreage and frequency in Akwapim South (Table 4.3).

Table 4.3—Frequency of Crop Cultivation

Crop	Freq.	Percent
Cassava	209	25.71
Maize	206	25.34
Pineapple	91	11.19
Others	307	37.76
Total	813	100.00

Notes: Frequency refers to the number of households in the full sample (for all three seasons) who cultivate a particular crop. Not all household cultivate each crop; however, it is worth noting that most households in the data cultivate at least 2 crops.

4.3 Idiosyncratic Shocks Experienced by Households in Akwapim South

The survey period for the data collection covered three growing seasons for maize. Most households in the four villages cultivate maize at least twice a year. Due to the pattern of rainfall distribution over the year, households have a fixed calendar for maize cultivation. The first growing season begins in March while the second begins in September. Maize normally matures in about three months after planting and therefore June-July and November-December are harvesting periods for the major and minor maize seasons, respectively.

During the season households experience different types of idiosyncratic shocks which include damage to crops in storage and in the field, unexpected household expenses, negative health events, loss of productive assets, and theft of crops in the field. Data were collected on shocks by asking respondents to self-report negative events they experienced in the previous round. Crops in storage include maize, yams, cassava and other crops harvested by the household. Examples of unexpected household expenses are funeral expenses, church donation, and unexpected increase in prices. Table 4.4 presents summary statistics for the incidence of idiosyncratic shocks over the three seasons considered. Only a small percentage of households experienced shocks in season 1 and season 2. No shocks were reported except for unexpected expenses, damage to crops and negative health events. Negative health events are experienced in all three seasons, however, only a very small percentage (as low as 0.08%) of households experienced these shocks. Plot level shocks are divided into damage to maize and damage to other crops in the field. Sources of damage to crops include insect attacks, fire, disease attacks, and scorching. As a consequence of the nature of certain types of idiosyncratic shocks, they can lead to large effects on labor allocation and subsequently on crop yields.

Table 4.4—Idiosyncratic Shocks Experience by Household in Sample

Variable	Percentage of Households/Plots Season 1	2	3
Plot Level Shocks			
Damage to maize in previous harvest and preharvest period	0	0	0
Damage to maize in planting period	0	2.67	1.89
Damage to other crops in previous harvest and preharvest period	0	0	5.66
Damage to other crops in planting period	1.42	16	11.32
Household Level Shocks			
Damage to stored crop in previous harvest and preharvest period	0	0	4.35
Damage to stored crop in planting period	0	0	30.43
Unexpected expenses in previous harvest and preharvest period	0	0	0
Unexpected expenses in planting period	1.02	0	56.52
Negative health events in previous harvest and preharvest period	0.08	0.41	0.11
Negative health events in planting period	0.18	0.52	0.3

Notes: The planting period is the period from planting until crop establishment. The pre-harvest period is the period after crop establishment until maturity while the harvest period refers to the period during which harvesting takes place. All variables are dummies: takes a value of 1 if the shock occurred and 0 if otherwise.

The data for idiosyncratic shocks are divided into periods (planting, preharvest, and harvest) based on the maize growing season. This has the benefit of making it easier to incorporate information on ex post shocks into the analysis. Hence information on shocks from the second part of the previous season (preharvest and harvest period) is taken into consideration by the household when they make decisions on maize production for the first part (planting period) of the current season.

4.4 Household Crop Production Decisions, Uncertainty, and Idiosyncratic Shocks

Previous studies have established the significance of the role played by uncertainty in agricultural production decisions. Due to the sequential nature of the agricultural production process, risk averse farmers consider temporal risk when making decisions. Figure 4.2 presents a kernel density plot of maize yield for all three seasons considered. The plot shows a significant change in the variance of yield over the three seasons. The standard deviations of maize yields (plot level) for the season 1, 2, and 3 were 116.48, 91.84, and 81.81 kg per acre, respectively, while the means were 78.74, 68.11, and 76.48 kg per acre, respectively (see Table 4.5). These high coefficients of variation for yield (see Table B.2) indicate that maize production is highly risky and that risk varies by season.

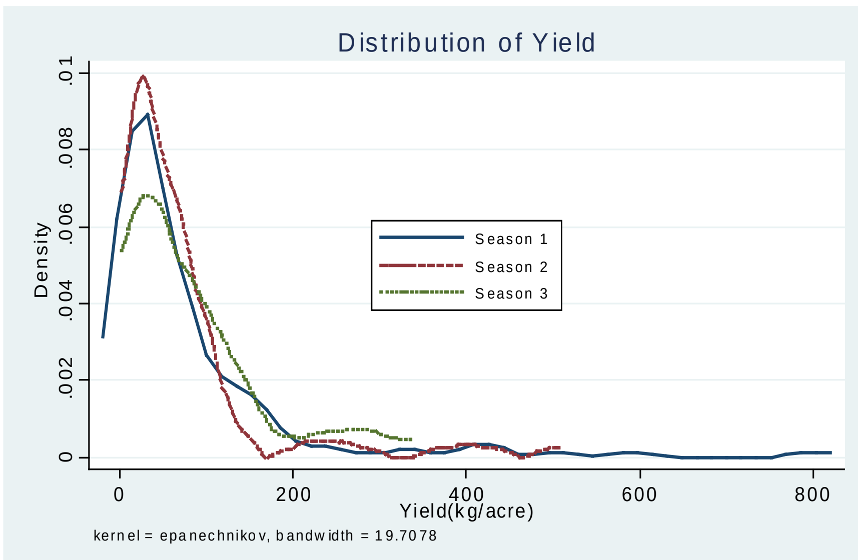

Figure 4.2—Distribution of Household Maize Yield

Table 4.5 reports descriptive statistics for household production, household characteristics and risk. For each of the seasons considered in the analysis for this study, about 85% of household heads had at least one year of schooling. The same situation applies to occupation: 90% of household heads in the sample are farmers. The average age is about 43 years. The average planting period non-farm labor for seasons 1, 2 and 3 were 4.96, 0, and 21.25 days, respectively. The zero value for season 2 is as a result of households not reporting their planting period non-farm labor. In the case of the preharvest period non-farm labor, households report non-farm labor activity for only season 2. These low levels of non-farm labor mean that non-farm income constitutes a small portion of total household income. Season 2 is relatively shorter than season 1 and 3 which are both major rainy seasons.

Table 4.5—Descriptive Statistics for Production, Household Characteristics and Risk

	Mean		
Variable	Season 1	Season 2	Season 3
Production			
Maize yield (kg/acre)	78.74	68.11	76.48
Planting labor (days/acre)	3.51	6.47	11.59
Preharvest labor (days/acre)	11.95	10.19	17.81
Acreage	5.28	5.76	3.68
Household Characteristics			
Occupation (1 if head is a farmer and 0 if otherwise)	0.90	0.88	0.91
Education (1 if head had schooling and 0 if otherwise)	0.88	0.83	0.85
Planting period non-farm labor (days/acre)	4.96	0.00	21.26
Preharvest period non-farm labor (days/acre)	0.00	24.92	0.00
Planting period farm income (¢)	347000	379000	534000
Preharvest period farm income (¢)	272000	103000	209000
Initial Wealth (¢)	1470000	1080000	2710000
Risk Measure of Maize Yield (standard deviation)			
Standard deviation of maize yield (kg/acre)	116.48	91.84	81.81

Comparison of the distribution of input allocation for each of the three seasons provides evidence of household response to uncertainty. Figure 4.3 and 4.4 display kernel density plots of plot level labor use in maize production for each of the three seasons. Given that most household heads are farmers, one might expect relative stability in the amount of labor allocated per acre of land cultivated. However, Figure 4.3 shows a drastic change in the distribution of planting labor per acre from season to season.[12] Season 1 is skewed to the left and has a shorter tail as compared to those of seasons 2 and 3. The high number of zero- or near-zero-valued observations recorded for the planting period of season 1 is probably as a result of transient measurement

[12] See Table B.2 of Appendix B for the coefficients of variation for planting period labor for each of the three seasons.

errors in recording labor in the first survey round or two. Another explanation is under-reporting by respondents in the first few survey rounds. One possible sources of this change in distribution is yield uncertainty and the experience of negative events at the household and plot level.

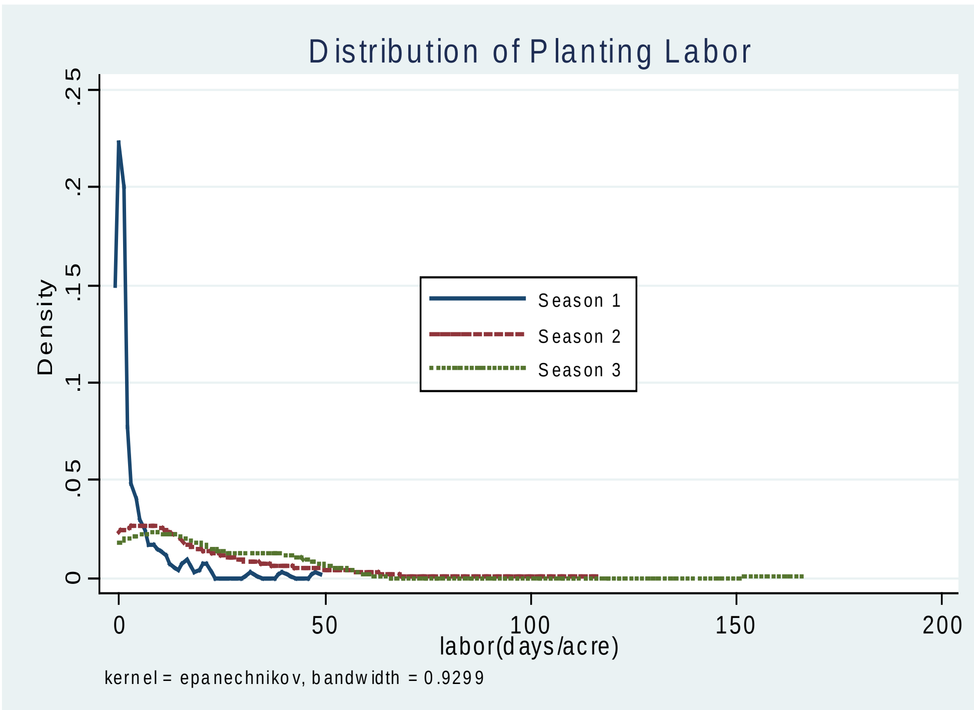

Figure 4.3—Distribution of Household Planting Period Labor Allocation

Preharvest labor is comparatively more stable in terms of the variation for each season.[13] Figure 4.3 represents kernel density plots for each season. There is a gradual shift in the distribution of preharvest labor. The plot for season 3 has longer tails than the first two seasons.

[13] See Table B.2 of Appendix B for the coefficients of variation for preharvest period labor for each of the three seasons.

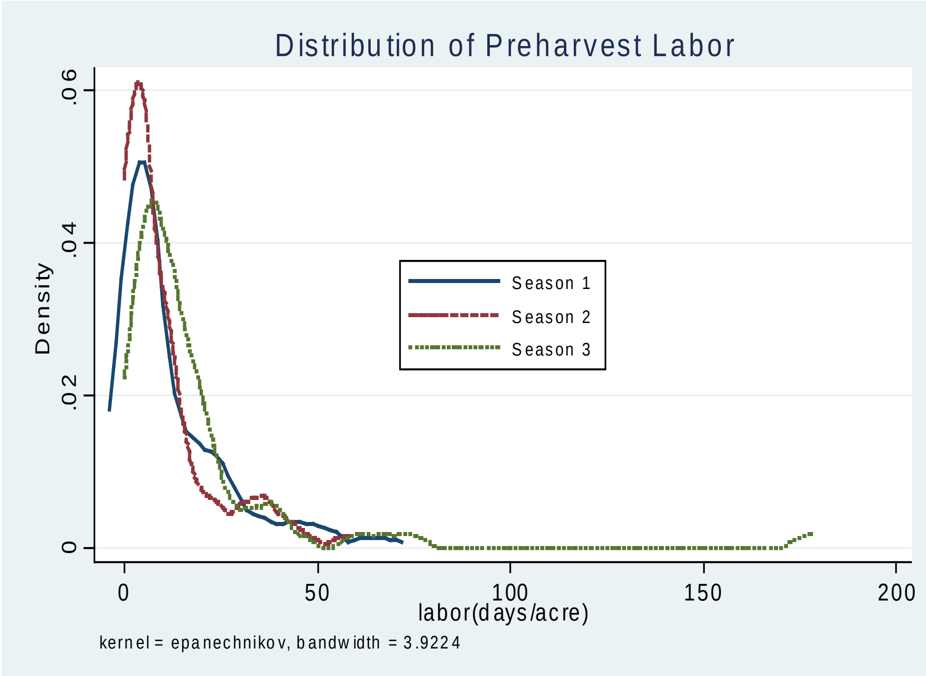

Figure 4.4—Distribution of Household Preharvest Period Labor

Table 4.6 gives an outline of the maize production decision making process of smallholder farm households in Akwapim South. For this thesis, I make the simplifying assumption that the effects of idiosyncratic shocks do not persist beyond the current or immediately subsequent season. During the preseason (before planting in March) period, the household experiences shocks (s_0) that are taken into account when making crop production decision (land preparation, planting and weeding) in the first planting period (March 1997). Shocks (s_0, s_1) experienced by the household during the planting period of season 1, and the preharvest and harvest period of the previous season are considered when making decisions in the first preharvest period (April-June 1997). Labor allocated during the harvest period is very likely to be proportional to yield. Therefore, idiosyncratic shocks are likely to have an insignificant effect on harvest period labor. From experience the household knows the required amount of labor per acre for harvesting maize in the field.

Table 4.6—Household Maize Production Calendar and Decision Making

	SEASON 0	SEASON 1			SEASON 2			SEASON 3		
PERIOD	Harvest Period	Planting Period	Preharvest Period	Harvest Period	Planting Period	Preharvest Period	Harvest Period	Planting Period	Preharvest Period	Harvest Period
MONTH	Nov-Feb	Mar	Apr-Jun	July	Aug	Sep-Dec	Jan	March	April-Jun	July
SURVEY ROUNDS	1-3	4	5	6	7	8-9	10	11	12-14	15
MAIN ACTIVITY	None	planting, land preparation, weeding	weeding, other farm operations	Harvest	planting, land preparation, weeding	weeding, other farm operations	Harvest	planting, land preparation, weeding	weeding, other farm operations	Harvest
SHOCKS	s_0	s_1	s_2		s_3	s_4		s_5	s_6	
TYPE OF DECISION RULE	---	Ex ante	Ex post	---	Ex ante	Ex post	---	Ex ante	Ex post	---
NEW SHOCK INFO ARRIVING	I assume harvest labor is proportional to produce.	s_0	s_0 , s_1	I assume harvest labor is proportional to produce.	s_2	s_2 , s_3	I assume harvest labor is proportional to produce.	s_4	s_4 , s_5	I assume harvest labor is proportio-nal to produce.

s_0, s_2, s_4, s_6 : Shocks experienced by household in the preharvest and harvest period of the previous season e.g., damage to crops, unexpected household expense.

s_1, s_3, s_5 : Shocks experienced by household in the planting period of the current season

In the season 2, when households are making crop production decisions in the planting period (August 1997) they consider shocks (s_2) that were realized during the preceding preharvest (April to June 1997) and harvest (July 1997) period. On-farm labor allocation for the preharvest period of season 2 (September to December 1997) are made by the household taking into account shocks (s_2, s_3) experienced during the previous season preharvest and harvest (April to July 1997) as well as early season planting (August 1997) periods. Decisions made by the household in season 3 follows the process described for season 1 and 2.

CHAPTER 5

EMPIRICAL ESTIMATION STRATEGY

5.1 The Household Crop Production Model

In Akwapim South, households use land, labor and very small amounts of chemical inputs in maize production. I assume that acreage decisions are made before the beginning of the season while labor allocation decisions are made during the season. During the season, the household experiences both idiosyncratic and covariate shocks that affect total household production. Due to the similarities in covariate shocks such as weather, and prices experienced by households, only estimates of the effects of idiosyncratic shocks on crop yield can be identified. In this study, I assume that unobserved idiosyncratic shocks are exogenous, independent and identically distributed and jointly normal with zero mean and variances (Fafchamps, 1993). Labor is allocated sequentially during the season as expected shocks and other information relevant to labor allocation are revealed to the household. We also assume that households have identical crop production technologies and responses to covariate shocks.

I estimate the household maize production technology using a generalized quadratic functional form. The quadratic functional form was chosen due to the occurrence of zero labor allocation after aggregation of the data. Therefore, we express the household's crop production technology for maize as:

$$y_{2ijt} = \beta_0 + \beta_1 l_{f1ijt} + \beta_2 l_{f1ijt}^2 + \beta_3 l_{f2ijt} + \beta_4 l_{f2ijt}^2 + \beta_5 l_{f1ijt} \cdot l_{f2ijt} + \beta_6 s_{0ijt} + \beta_7 s_{1ijt} + \beta_8 W_{0ijt} + \beta_9 W_{0ijt}^2 + \psi H_i + u_{ijt} \tag{26}$$

$$u_{ijt} = \pi_{ij} + e_{ijt}$$

where i refers to household, j plot and t season; H denote vectors of seasonal dummies, village and other household covariates which may affect crop production; π_i is the unobserved household plot-specific, time-invariant effect and e_{ijt} is the independent and identically distributed (iid), normally distributed unexplained portion of the random error with zero mean.

The stochastic structure of the household crop production technology is:

$$e_{ijt} \sim N\left(0, \sigma_{ijt}^2 I\right)$$

$$E\left(e_{ijt}, e_{ij\tau}\right) = 0 \qquad \text{where } t \neq \tau$$

$$E\left(e_{kjt}, e_{ijt}\right) = 0 \qquad \text{where } k \neq i$$

$$E\left(\pi_i X'\right) = 0 \qquad \text{where } X = \left(l_{f1ijt}, l_{f2ijt}, W_{0ijt}, s_{0ijt}, s_{1ijt}\right)$$

This specification allows the error term e_{ijt} to be heteroscedastic due to the relationship between traditional inputs and the probability distribution of crop yields (Appelbaum and Ullah, 1997; Just and Pope, 1979; Kumbhakar and Tveteras, 2003; Love and Buccola, 1991). Consequently, production technology parameters estimated using ordinary regression techniques in the presence of heteroscedasticity are consistent but inefficient. I solve the problem by using a weighted panel regression in a Just-Pope framework to correct for heteroscedasticity.[14] I use both random and fixed effects panel estimators. The results for the two methods are compared using Hausman's specification test. The elasticities of labor inputs are also compared. Using a panel regression approach has the benefit of helping us understand the role played by labor in the household crop production process as well as its effects on yield risk while controlling for unobserved household level differences in ability, outside employment

[14] This is similar to a weighted least square regression except that panel regression techniques are used instead of ordinary least square estimation.

options and plot level differences in time-invariant biophysical characteristics such as slope, distance from homestead, access to water, soil type, etc. I am also able to explore the importance of the timing of the occurrence of shocks in the household production process. We can rewrite the maize yield function in a Just-Pope form as:

(27) $$y_2 = f(X,H) + \pi_i + h^{\frac{1}{2}}(X,H)\varepsilon$$

where $E(\varepsilon) = 0; e_{ijt} = h^{\frac{1}{2}}(X,H)\varepsilon$

The first term represent the deterministic component of the household maize yield function while the last term represents the stochastic component. I correct for heteroscedasticity by dividing each term in regression equation (27) by $h^{\frac{1}{2}}(X,H)$ resulting in the expression:

(28) $$y_2 h^{-\frac{1}{2}}(X,H) = f(X,H)h^{-\frac{1}{2}}(X,H) + \pi_i h^{-\frac{1}{2}}(X,H) + \varepsilon$$

In an approach similar to that used by Just and Pope, I estimate equation (28) using a weighted panel regression by following the steps below:

(a) Estimate equation (26) using a panel regression to obtain estimates of the parameters of the crop production function. Use the estimates to generate residuals $\hat{e}_{ijt}$.

(b) Regress the square of residuals $\hat{e}_{ijt}^2$ from (a) on all the independent variable (X, H) and use the estimates to obtain $\hat{h}(X,H)$.[15]

(c) Divide each term of the original regression equation by $\hat{h}^{\frac{1}{2}}(X,H)$. Estimate equation (28) by regressing $y\hat{h}^{-\frac{1}{2}}(X,H)$ on all the independent variables divided by $\hat{h}^{\frac{1}{2}}(X,H)$.

[15] This is based on the relationship $E(\hat{e}_{it}^2) = E(\hat{h}(X,H)\varepsilon^2) = \hat{h}(X,H)$. The next section further discusses this and how to use the Just-Pope method to obtain ex ante yield risk. Note that $\hat{h}(X)$ denotes the estimate of $h(X)$.

The estimates resulting from the above econometric procedure are consistent, unbiased and asymptotically efficient. In this paper, I proceed a step further by repeating the above procedure until the standard errors of the coefficients of the regression converge.[16] This is because we don't know the true functional form of $h^{\frac{1}{2}}(X,H)\varepsilon$. In the next section, I use the first two steps of the above econometric procedure to estimate risk and also explore the effect of on-farm labor allocation on risk.

5.2 *Just-Pope Method for Estimating Yield Risk*

In this paper, I use the conditional yield variance as a measure of the yield risk faced by households in the crop production process. I estimate two types of risk: ex ante yield risk and ex post yield risk. The conditional variance of yield is estimated using the Just-Pope method just described. According to Just and Pope (1979), by specifying the crop production function as in (27), where mean yield, $E(y) = f(X,H)$ and variance of yield, $v(y) = \sigma_y^2 = h(X,H)$ the effects of inputs on mean and variance of yield can be independent. Therefore the marginal effect of labor on variance and crop output are not determined *a priori*.

The estimation procedure for the conditional variance of maize yield based on Just and Pope (1979) is described below. Let's rewrite the Just-Pope yield function more compactly as:

(29) $$\upsilon = h^{\frac{1}{2}}(X,H;\delta)\varepsilon = y - f(X,H;\alpha)$$

[16] Refer to section D.1 of Appendix D for details of this iterative procedure for correcting heteroscedasticity as well as its basis.

where α and δ represent the coefficients of the deterministic and stochastic components of the crop production function, respectively. Since the estimates of the parameters of the household crop production technology $\hat{\alpha}$ and $\hat{\delta}$ are consistent, $\upsilon *$ consistently estimates the stochastic component of the technology. We obtain:

(30) $$\upsilon * = \hat{h}^{\frac{1}{2}}\left(X, H; \hat{\delta}\right)\varepsilon = y - \hat{f}\left(X, H; \hat{\alpha}\right)$$

Taking expectations after squaring $\upsilon *$:

(31) $$E\left\{(\upsilon *)^2\right\} = \hat{\sigma}_y^2 = E\left\{\hat{h}\left(X, H; \hat{\delta}\right)\varepsilon^2\right\} = \hat{h}\left(X, H; \hat{\delta}\right)$$

Based on the works of Just and Pope as well as Hildreth and Houck, the expression in (31) can be used in a regression equation as follows:

(32) $$(\upsilon *)^2 = E\left\{\left(\upsilon_c^*\right)^2\right\} + \omega = \hat{h}\left(X, H; \hat{\delta}\right) + \omega$$

where $E(\omega) = 0$ by definition of expectations. ω represents all random exogenous shocks which occur during the season which are assumed to be independently distributed with zero mean (Kumbhakar and Tveteras, 2003). Therefore we can get estimates $\hat{\alpha}$ and $\hat{\delta}$ by regressing $(\upsilon *)^2$ on all their corresponding independent variables using a linear functional form to approximate the conditional yield variance or yield risk function.[17]

As demonstrated by Just and Pope (1979), $\hat{V}(y) = \hat{h}\left(X, H; \hat{\delta}\right) = (\upsilon *)^2 = \hat{\sigma}_y^2$ which represents the yield risk faced by the household. Therefore, $\hat{\delta}$ represent the coefficients which reflect the risk effect of on-farm labor allocated by the household to maize production. This is similar to using a weighted least squares regression to

[17] Kumbhakar and Tveteras, (2003) used a Just-Pope production function $y = f(X) + g(X)\varepsilon$ to develop an output risk function of the form $g(X)$. They describe ε as a stochastic term which represents random production shocks.

estimate the stochastic (variance) component of yield (Griffiths and Anderson, 1982[18]; Just and Pope, 1979). Note that ordinary least square estimation is used for the second step of the procedure. By using panel regression techniques for the first stage, I am able to isolate the unexplained portion of random error.

5.3 Application of the Just-Pope Method in the Estimation of Yield Risk

In this thesis, I assume acreage decisions are made before the beginning of the season. When the household is making a decision on labor allocation per acre, they take into account their knowledge of yield risk at that time of the season. During the planting period, the household determines ex ante yield risk using information on shocks they experienced during the previous (preharvest and harvest) periods. Ex post risk is determined in the same way; however, the household updates its knowledge using information on shocks from the planting period of the current season. I use the Just-Pope method described in the previous section to estimate ex ante and ex post yield risk. In the estimation of yield risk, seasonal observations are pooled to take advantage of identification resulting from inter-seasonal, intra-household, plot-level, and cross-sectional variations among maize plots.[19]

[18]In their paper, Griffiths *et al.* (1982) specified the stochastic component of production as heteroscedastic. A similar specification is used in this paper.
[19] Refer to Appendix E for description of the estimation of ex ante and ex post yield risk.

The regression equation for estimating ex ante yield risk is written as:

$$(33)\quad V_{1ijt} = \theta_0 + \theta_1 W_{0ijt} + \theta_2 W_{0ijt}^2 + \theta_3 s_{0ijt} + \phi H + \rho_{ij} + \vartheta_{ijt}; E(\vartheta_{ijt}) = 0$$

where V_{1ijt} represents household conditional yield variance of maize in the planting period; ρ_{ij} is the household- and plot-specific time invariant effect; and ϑ_{ijt} is the random error term. I assume the yield risk function is general quadratic functional form. The regression equation for estimating ex post yield risk is written as:

$$(34)\quad V_{2ijt} = \varpi_0 + \varpi_1 W_{0ijt} + \varpi_2 W_{0ijt}^2 + \varpi_3 s_{0ijt} + \varpi_4 s_{1ijt} + \varphi H + \varsigma_{ij} + \kappa_{ijt}; E(\kappa_{ijt}) = 0$$

where V_{2ijt} represents household subjective variance of maize yield in the preharvest period; ς_{ij} is the household- and plot-specific time invariant effect; and κ_{ijt} is the random error term. I assume the risk function is quadratic in initial wealth.

I estimate equations (33) and (34) using both fixed and random effect regression method. I then compare the results of the two methods using a Hausman's test. The selected models are used to estimate the ex ante and ex post yield risk of the household. These estimated values ($\hat{V}_{1ijt}$ and $\hat{V}_{2ijt}$) are plugged into the household labor allocation model as estimators of household-plot- and season-specific yield risk. The estimation procedure for the household labor allocation model is described in the next section.

5.4 Specification and Estimation of Labor Allocation

I assume that the only risk the household deals with in their crop production is yield risk. I further assume that output price, hired labor wage rate, and input prices are known with certainty and all households face similar prices. These are reasonable assumptions given the proximity of the survey villages. Using equations (22) to (25) from the optimization problem and appending optimization errors (Chavas *et al.*, 1996; Saha *et al.*, 1994) to them, the household optimal on-farm labor allocation system can be specified as:

$$(35)\quad l_{f1ijt} = \omega_0 + \omega_1 s_{0ijt} + \omega_2 W_{0ijt} + \omega_3 W_0^2 + \omega_4 \sqrt{V_{1ijt}} + \omega_5 I_{1ijt} + \omega_6 I_{1ijt}^2 + \eta H + \mu_i^{lf1} + \varepsilon_{ijt}^{lf1}$$

$$(36)\quad l_{w1ijt} = \tau_0 + \tau_1 s_{0ijt} + \tau_2 W_{0ijt} + \tau_3 W_{0ijt}^2 + \tau_4 \sqrt{V_{1ijt}} + \tau_5 I_{1ijt} + \tau_6 I_{1ijt}^2 + \xi H + \mu_i^{lw1} + \varepsilon_{ijt}^{lw1}$$

$$(37)\, l_{f2ijt} = \gamma_0 + \gamma_1 l + \gamma_2 s_{0ijt} + \gamma_3 s_{1ijt} + \gamma_4 W_{0ijt} + \gamma_5 W_{0ijt}^2 + \gamma_6 \sqrt{V_{2ijt}} + \gamma_7 I_{1ijt} + \gamma_8 I_{2ijt} + \gamma_9 I_{1ijt}^2 + \gamma_{10} I_{2ijt}^2 + \chi H + \mu_{ijt}^{lf2} + \varepsilon_{ijt}^{lf2}$$

$$(38)\quad l_{w2} = \psi_0 + \psi_1 l + \psi_2 s_{0ijt} + \psi_3 s_{1ijt} + \psi_4 W_{0ijt} + \psi_5 W_{0ijt}^2 + \psi_6 \sqrt{V_{2ijt}} + \psi_7 I_{1ijt} + \psi_8 I_{2ijt} + \psi_9 I_{1ijt}^2 + \psi_{10} I_{2ijt}^2 + \varphi H + \mu_i^{lw2} + \varepsilon_{ijt}^{lw2}$$

$$E\left(\varepsilon_{ijt}^{lw1}\right) = E\left(\varepsilon_{ijt}^{lf1}\right) = E\left(\varepsilon_{ijt}^{lw2}\right) = E\left(\varepsilon_{ijt}^{lf2}\right) = 0\,;\, l = \left(\hat{l}_{f1ijt}, \hat{l}_{w1ijt}\right)$$

where μ_i^{lw1}, μ_i^{lf1}, μ_i^{lw2} and μ_i^{lf2} denote unobserved household-specific time-invariant effects for each model. I_0 denotes household exogenous income for the previous pre-harvest period and I_1 is income for the current (planting) period. Predicted values of prior period labor allocation $l = \left(\hat{l}_{f1ijt}, \hat{l}_{w1ijt}\right)$ for the planting period are used in regression equation (37) and (38) for the subsequent preharvest period instead of actually values; the error terms in (37) and (38) are likely to be correlated with planting period labor allocations. When the household makes labor allocation in the preharvest period, their decision is influenced by errors in allocation from the planting period. As a result, errors in planting period labor allocation regression equations are correlated with their corresponding equations for the preharvest period. Estimating the first two regressions and using them to predict the planting period labor allocation removes these errors.

Equations (35) to (38) are estimated independently using fixed and random effects regression techniques. This involves estimating the first two regression equations representing households ex ante labor decision rules and using them to obtaining linear predictions for labor allocation which are then plugged into the last two equations before they are estimated. The error terms are independent across equations and the regressors are identical within period; therefore joint estimation does not improve efficiency of estimates. The errors terms are likely to be heteroscedastic since households differ in their ability to optimally allocate labor to crop production and the labor market. I correct for heteroscedasticity using the procedure described in section 5.1.

Another issue is omitted variables due to lack of consumption and labor availability data by period: $C_1, C_2, \overline{C}_1, \overline{C}_2, L_1, L_2, \overline{L}_1, \overline{L}_2$ and other household covariates (e.g., number of household members, soil fertility, cropping system, planting date, quality of labor) are missing in regression equations (35) to (38). Most households do not have observations for certain types of idiosyncratic shocks (Table 4.4) for some rounds and are dropped from the analysis. Hence, the effects of certain types of idiosyncratic shocks are considered for only one of the two periods. The lack of data on shocks might be as a result of missing data or simply the failure of households to report incidence of certain types of shocks. Consequently, estimates of the model might be inaccurate due to omitted variable bias. However, the use of panel regression techniques reduces this bias substantially. Most of the bias is picked up by the estimated fixed or random effects.

Labor is aggregated into periods but I am not able to take into account planting date due to lack of data on planting dates. Variation in planting date and calendar for other on-farm activities can lead to the problem of measurement errors which also bias coefficient estimates.

CHAPTER 6

RESULTS AND DISCUSSIONS

The results can be divided into three groups: household yield, conditional yield variance, and labor allocation. I first examine the household yield function estimated using random effects regression with corrections for heteroscedasticity and cluster effects.[20] Estimates of elasticity and marginal physical products of labor allocation in the planting and preharvest periods are examined. This is followed by the discussion of the household conditional yield variance function and marginal yield risk effects of labor and initial wealth. Finally, I use the estimated household labor allocation models to analyze the ex ante and ex post effects of idiosyncratic shocks and risk.

6.1 Household Crop Production Technology

Table 6.1 presents the results of the estimation of the household maize yield function. Estimates of fixed and random effects are reported for comparison. Comparing the estimates of random effects (RE) and fixed effects (FE) model, it is evident that the estimates differ in magnitude and even signs. Under the FE model, the estimated coefficients for planting and preharvest period labor are negative with preharvest labor statistically significant at a 5% level. The overall R-square value for random effects is higher than the one for the fixed effects model. The random effects estimates are

[20] Standard errors are adjusted for cluster effects. The within-individual cluster effect results from the household cultivating the same plot from one season to another. The three seasons captured by the data set are adjoined to one another (see Appendix A for details).

consistent since unobserved household plot-specific time-invariant effects are likely to be uncorrelated with included variables. Therefore, I focus on the random effects estimates in my discussion of the results. The fraction of variation (Rho) explained by individual effects is high for both models. In addition to the above comparisons, I consider the marginal physical products (MPP) and elasticities for labor and initial wealth at the means of the sample (reported in Table 6.2)[21].

[21] Check section F.1 of Appendix F for details on the MPP and elasticities of selected variables.

Table 6.1—Household Maize Yield Function

Variables	Random Effects	Fixed Effects
On-farm Labor Allocation		
Planting period labor (days/acre)	2.489***	-0.00171
	(0.594)	(1.363)
Square of planting period labor $(\text{days/acre})^2$	0.0162	0.0460
	(0.0501)	(0.0345)
Preharvest period labor (days/acre)	2.636***	-2.037**
	(0.991)	(0.857)
Square of preharvest period labor $(\text{days/acre})^2$	-0.00217	0.00605
	(0.0174)	(0.0262)
Planting labor × preharvest labor $(\text{days/acre})^2$	-0.0752	0.0705
	(0.0951)	(0.0775)
Village and Seasonal Dummies		
Darmang	40.51**	
	(17.80)	
Pokrom	-15.54	
	(18.49)	
Oboadaka	19.25	
	(11.92)	
Season 1 (March 1996 to July 1997)	-14.23	-4.384
	(12.24)	(18.66)
Season 2 (August 1997 to January 1998)	-38.49***	-12.54
	(13.59)	(17.18)
Idiosyncratic Shocks (Dummy Variables)		
Damage to stored crops in planting period	-45.07**	0.0325
	(21.65)	(24.99)
Damage to other crops in planting period	16.33	5.871
	(15.97)	(22.45)
Negative health events in previous preharvest and harvest period	5.332	5.896
	(6.902)	(5.949)
Negative health events in planting period	6.080	5.574
	(6.190)	(10.50)
Unexpected expenses in planting period	-45.98**	-71.93***
	(20.66)	(15.53)
Household Characteristics		
Occupation (1 if household head is farmer, 0 if otherwise)	35.73*	
	(20.38)	
Education (1 if household head had some schooling, 0 if otherwise)	6.387	
	(15.46)	
Age of household head	-0.603	
	(1.194)	
Square of age of household head	0.00241	
	(0.0155)	
Initial wealth × 1,000,000 (¢)	11.9	9.15
	(9.08)	(6.47)
Square of initial wealth × 10^{13} $(¢)^2$	-5.18	-5.08
	(4.36)	(4.40)
Constant	4.578**	11.95***
	(1.923)	(1.404)
Observations	269	269

Table 6.1 (Continued)

	Random Effects	Fixed Effects
R-squared (before heteroscedasticity correction)		
Within	0.3367	0.7619
Between	0.2149	0.0018
Overall	0.2111	0.0024
Rho (fraction of variance due to individual effects u_i)	0.9366	0.9765
Number of pid	238	238
Joint Wald Test of Hypothesis (Prob>chi2)		
Idiosyncratic shocks	0.3216	0.4687
Initial wealth and square of wealth	0.1889	0.1585

Robust standard errors in parentheses are adjusted for cluster effects and corrected for heteroscedasticity using the iterative correction procedure described in section D.1 of Appendix D.
*** p<0.01, ** p<0.05, * p<0.1

The estimates of marginal physical product (MPP) for the RE model are also more reasonable than those for the FE model; the MPP for preharvest planting labor (at the sample mean) estimated under fixed effects is negative. As discussed earlier, the mean age of household heads is about 43 years and 90% of them are farmers. Consequently, one would expect elasticities between 0 and 1 since most farmers are very experienced and know how to grow maize properly. This suggests crop production by these households might be taking place in stage 2 of a classical production function. In terms of yield, on-farm labor allocation decisions during the preharvest period are slightly (but not statistically significant) greater than planting period on-farm labor.

Table 6.2—Estimated Marginal Physical Productivity and Elasticity for Maize Yield

	Marginal Physical Product		Elasticity	
Variable	Random Effects	Fixed Effects	Random Effects	Fixed Effects
Planting period labor (days/acre)	1.73	1.43	0.15	1.01
Preharvest period labor (days/acre)	2.14	-1.47	0.38	-2.19
Initial household wealth × 10,000 (¢)	0.10	0.07	0.24	1.49

Notes: Marginal physical product $MPP = \partial y / \partial x_i$. Elasticity $E_i = \partial y / \partial x_i \cdot (x_i / y)$ is evaluated at the means of independent variables.

Both the random and fixed effects MPP estimates of initial household wealth at the means are extremely low; however, they have reasonable elasticity values with respect to initial household wealth (Table 6.2). Initial household wealth has an estimated elasticity of 0.244 for random effects and 1.48 for fixed effects. From Table 6.1, initial household wealth does not significantly influence maize yields. The implication is that *ceteris paribus* richer households do not enjoy higher maize yields compared to their poorer counterparts. Table 6.1 reports the p-value (0.189) of the joint significant test of initial wealth and its square. So we reject the hypothesis that self-insurance capacity proxied by wealth affects maize yields.

From the random effects estimates in Table 6.1, planting and preharvest period labor positively influence maize yields and are significant at the 1% level. The interaction term between planting and preharvest period labor does not significantly affect yield and has a negative sign. The negative sign indicates planting and preharvest period labor are technically substitutes.

The village level dummies in Table 6.1 encompass village characteristics that can potentially affect yield. These village characteristics include access to extension services, farming tools, topography, soil fertility and other unobservable variables. The dummy variable for Darmang has a large positive coefficient and is significant at the 5% level. One possible reason is that among all the villages, Darmang is the closest to the district capital, Nsawam. The coefficient for Darmang is 40.51 kg/acre. The dummy variable for season 2 also has a large significant effect on yield.

Maize yield in season 2 are about 40 kg/acre higher on average than maize yields in other seasons. This is difficult to interpret since the data do not contain information on weather and events which can potentially influence yields.

The coefficients for damage to stored crops and unexpected expenses in the planting period of the current season are statistically significantly (at the 5% level) different from zero. They have very strong negative effects as compared to labor and other variables which have significant effects on yield. Damage to stored crops in the planting period has a coefficient of -45.07 kg/acre while unexpected expenses in the planting period have a coefficient of -45.98 kg/acre. The mean yield for households in the sample is about 75 kg/acre.[22] Hence, when idiosyncratic shocks occur they have the potential of drastically reducing maize yields. The statistically significant effects of damage to stored crops and unexpected expenses in the planting period may be attributed to their direct effects on the household's stock of planting materials and cash budget, respectively. Unexpected expenses decrease the amount available for crop production while damage to stored crops (which is largely maize) decreases the household's stock of planting materials. Due to its long shelf life, maize is stored to be later used by the household for food and planting materials. Hence unexpected expenses and damage to stored crops in the planting period reduces the labor quality which in turn reduces crop yields.

In rural areas such as Akwapim South, sources of unexpected expenses include funerals and other social obligations, and unexpected increase in the cost of farm implements. When households incur unexpected expenses, it is likely to be accompanied by a decrease in consumption, use of inferior farm tools and other actions which can directly impact the productivity of labor. Behrman *et al.* (1997) found evidence of small productivity effects of caloric consumption in the planting stage that is realized in the harvest stage. Estimated coefficients for damage to other crops in the planting period, and negative health events in the planting and preharvest periods are not significantly different from zero. A joint test[23] of the effect of all the idiosyncratic shocks on yield failed to reject the null hypothesis that idiosyncratic

[22] Table B.1 of Appendix B contains descriptive statistics for important variables used in the analysis.
[23] Check section G.2 of Appendix G for details of the results of the Wald test.

shocks do not collectively affect yield; the p-value of the Wald test statistic is 0.3216. In general, the yield effect of an idiosyncratic shock depends on the type and the period in which the shock occurred.

From the RE model, most of the household variables do not significantly affect yield except for occupation (1 if household head is a farmer and 0 if otherwise) which is statistically significant (at the 10% level), with coefficient estimates of 35.58 kg/acre. The magnitude of the coefficient likely shows that technical knowledge of maize production has a very strong effect on yield. They are able to make better decisions with regards to timing of weeding, planting distance, land preparation, selection of suitable locations for farming, and other important factors in maize production. The dummy variable for whether the household head has ever been to school (education) has a positive effect on yield but is not significant. This is surprising since education typically improves the managerial ability of farmers making it easier for them to process information and reach good decisions.

Age of the household head, apart from being a proxy for experience, also represents other unobservables such as aversion to new technologies or techniques, ability to closely supervise farm work and other relevant characteristics which may be related to age. This may partly explain the confounding effects of age on yield which is negative and does not have a significant effect. It is expected that since most household heads are farmers with an average age of 43 years, age is a good proxy for experience and as a result should have a positive effect on yield; however, in this case age has a negative effect.

6.2 The Household Conditional Maize Yield Variance Function

The estimates of the coefficients of the household conditional yield variance function are reported in Table 6.3. The Breusch-Pagan test[24] for heteroscedasticity reveals that errors are heteroscedastic (p-value is less than 0.001). I correct for heteroscedasticity using iterative correction previously described. For the purpose of comparison, heteroscedasticity is also corrected using the White's correction.[25] The results of the method are reported in Table 6.3. The estimated coefficients are used for estimating marginal risk effects and elasticites for labor and initial wealth at the means of the sample. The results are reported in Table 6.4.

[24] Check section G.3 of Appendix G for results of the Breusch-Pagan Test.
[25] Refer to Table E.5 of Appendix E for estimates of both the iterative and Huber-White correction.

Table 6.3—Estimation of Conditional Yield Variance for Maize

Variables	Iterative Correction
On-farm Labor Allocation	
Planting period labor (days/acre)	18.37***
	(2.241)
Square of planting period labor (days/acre)^2	-0.0259
	(0.0630)
Preharvest period labor (days/acre)	0.538
	(2.201)
Square of preharvest period labor (days/acre)^2	0.0182
	(0.0261)
Planting labor × preharvest labor (days/acre)^2	-0.233*
	(0.133)
Village and Seasonal Dummies	
Darmang	145.6***
	(53.10)
Pokrom	5.664
	(50.62)
Oboadaka	23.55
	(41.59)
Season 1 (March 96 to July 97)	186.7***
	(59.89)
Season 2 (August 97 to January 98)	66.42
	(63.93)
Idiosyncratic Shocks (Dummy Variables)	
Damage to stored crops in planting period	-23.13
	(113.8)
Damage to other crops in planting period	3.960
	(84.84)
Negative health events in previous season	70.83*
	(38.32)
Negative health events in planting period	32.53
	(41.71)
Unexpected expenses in planting period	76.46
	(116.1)
Household Characteristics	
Occupation (1 if head is farmer, 0 if otherwise)	-22.79
	(52.80)
Education (1 if head had some schooling, 0 otherwise)	0.771
	(41.06)
Age of household head	-3.405
	(3.925)
Square of age of household head	-0.0179
	(0.0461)
Initial wealth× 100,000 (¢)	7.57***
	(2.22)
Square of initial wealth × 1,000,000,000 (¢)^2	-0.003***
	(0.001)
Constant	-0.0891
	(0.0674)
R-squared	0.104
Joint Test of Idiosyncratic Shocks (Prob > F)	0.47

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

According to Table 6.4, the marginal risk effect and elasticity of initial wealth for both estimation methods are similar. The risk effect of initial wealth is very weak; however its elasticity is higher than that for labor. The coefficient for the square of initial wealth is negative for both methods; this indicates that households with initial wealth greater than a critical value (¢10,939,306) can benefit from a very weak risk-decreasing effect of initial wealth.[26] In other words, the marginal effect of initial wealth on risk is negative for relatively richer households in the sample and positive for poor ones (with initial wealth less than ¢10,939,306). Only 7 households in the subsample have wealth beyond this level.[27] The positive marginal effect of initial household wealth on yield risk for most households in the sample (94%) indicates that wealthier households face higher yield risk compared to poor ones. This is likely to be as a result of wealthier households engaging in other activities that distract them from maize production culminating in higher yield risk.

The estimates for the marginal risk effects of labor under iterative correction seem reasonable. Since the preharvest period is longer than the planting period, farmers have more opportunities to update their production decisions, thus giving them more control over the production process. Based on the estimates under iterative correction at the mean of the sample, planting period labor allocation is risk-increasing while preharvest period labor has a risk-decreasing effect. The significant effect of labor on yield variance is consistent with the finding by Antle (1983) that the first three moments—this thesis focuses on only the first two—of output is a statistically significant function of inputs.

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[26] This can be obtained by simply solving for the value of initial wealth that satisfies the condition: $\partial\sigma^2/\partial W_0 = \left(7.57\times10^{-5}\right) - 2\cdot\left(3.46\times10^{-12}\cdot W_0\right) < 0 \Rightarrow W_0 > \dfrac{7.57\times10^{-5}}{2\times3.46\times10^{-12}} = 10939306$

[27] Refer to Figure B.5 of Appendix B.

Table 6.4—Estimated Marginal Risk Effects and Elasticities for Labor and Initial Household Wealth

	Marginal Risk Effect		Elasticity	
Variable	White	Iterative	White	Iterative
Planting period labor (days/acre)	4.19	15.12	0.18	0.53
Preharvest period labor (days/acre)	4.80	-0.38	0.44	-0.03
Initial household wealth × 10,000 (¢)	0.05	0.06	0.67	0.64

The coefficient for planting period labor (18.37) is significant (at 1% level). This may be attributed to the fact that there is a positive relationship between planting labor allocated per acre and the number of maize plants per acre (closer planting distance). Therefore, the more maize planted per acre, the more risk faced by the household. The closer the planting distance, the more vulnerable plants are to diseases, and other plot-specific shocks. Planting and preharvest period labor interact to have a negative effect on yield risk. The interaction term for planting and preharvest period labor is negative and significant (at 10% level). Therefore, the coefficients for the interaction term, planting period labor and its square can have a combined negative effect for some combinations of planting and preharvest labor.

There is evidence of seasonal and village effects on yield risk. The dummy variables for Darmang and season 1 both have a significant positive effect on yield risk (at 1% level). Under iterative correction, the value of the coefficient for Darmang is 145.6 and 186.7 for season 1. These two variables have the strongest effects on yield risk. This suggests location and time are very important when considering yield risk faced by different households. All the coefficients for village and seasonal dummies estimated using iterative correction have positive effects on yield risk.

Certain types of idiosyncratic shocks are expected to have positive effects on yield risk. Only negative health events in previous preharvest and harvest period have a significant effect on yield risk. The coefficient has a value of 70.83 and is significant at the 10% level. All the other idiosyncratic shocks do not significantly affect yield risk. I test the hypothesis that idiosyncratic shocks have a joint effect on yield risk using a Wald test.[28] The p-value of the test statistic is greater than 0.05; I therefore conclude that idiosyncratic shocks do not collectively influence yield risk faced by the households (Table 6.3). The dummy variable representing unexpected expenses incurred during the planting period has the largest coefficients but it is not significant even at the 10% level. The effects of idiosyncratic shocks on yield risk suggest the presence of alternative mechanisms which mask the risk effects of idiosyncratic shocks. The significant effect of negative health events in the preharvest and harvest period of the previous season means either mechanism adopted by household do not effectively deal with negative health events or they simply do not have mechanisms for dealing with negative health events.

The other variables representing household characteristics (except education) have the expected signs but do not statistically significantly affect yield risk. Both age and occupation have negative effects. I argue that age is a good proxy for many characteristics including experience while occupation is a good proxy for farming ability. In effect, households whose heads are farmers *ceteris paribus* should face less yield risk than those with heads who are not farmers. Older household heads are less likely to experiment with new technologies (e.g., new varieties, organic fertilizers) than younger ones and this reduces the households' exposure to risk by reducing the probability of change in yield. Education is a special case since it is known to improve the managerial ability of farmers. However, it gives the household head more employment opportunities which can divert their attention and consequently reduce the quality of labor. The possibility of divided attention can lead to an increase in the variation of yield. This is consistent with Barrett *et al.* (2006) finding that secondary education has a negative influence on technical efficiency among West African rice farmers.

[28] Refer to section G.2 of Appendix G for test statistics for the Wald test.

6.3 The Household Labor Allocation Model for Planting and Preharvest Periods

Regression equations (35) to (38) represent the household labor allocation model for the planting and preharvest period. These are estimated independently using random effects regression techniques. Estimates of the coefficients for the household labor allocation model for the planting period (*ex ante*) are reported in Table 6.5. The results of the estimation of the household labor allocation model for the preharvest period (*ex post*) are reported in Table 6.7. Using the results of the *ex ante* and *ex post* labor allocation model, I test the hypotheses regarding labor allocation posited at the end of the section 3.1.[29] Estimates of the marginal effects and elasticities of selected variables at the sample means are reported in Table 6.6 and 6.8.

[29] Refer to section G.2 of Appendix G for the test statistic of the Wald Test.

Table 6.5—Household Labor Allocation Model for Planting Period

Variables	On-Farm Labor	Non-Farm Labor
Farm Characteristics		
Percentage of acreage in maize	-28.26**	-33.26
	(14.31)	(23.99)
Square of percentage in acreage	23.06*	28.92
	(12.96)	(18.63)
Idiosyncratic Shocks and Ex ante Yield Risk		
Negative health events in previous season	0.341	-0.374
	(2.334)	(1.714)
Standard deviation of yield	-0.549	0.645
	(0.651)	(0.698)
Village and Seasonal Dummies		
Darmang	2.980	4.833
	(3.988)	(3.557)
Pokrom	2.117	38.30
	(3.423)	(24.77)
Oboadaka	-0.582	-2.441
	(1.915)	(4.003)
Season 1 (March 96 to July 97)	-9.080***	-6.929**
	(3.524)	(3.485)
Season 2 (August 97 to January 98)	-9.354	-3.670
	(6.610)	(6.724)
Household Characteristics		
Planting period income × 1,000,000 (¢)	-1.23	7.36
	(1.51)	(4.81)
Square of planting period income × 10^{12} (¢)	0.10	-0.96
	(0.12)	(0.62)
Occupation of household head	2.084	5.602
	(1.818)	(3.990)
Education of household head	1.238	0.161
	(2.851)	(3.911)
Age of household head	0.0366	-0.110
	(0.0862)	(0.146)
Initial household wealth × 1,000,000 (¢)	0.76	-0.78
	(1.06)	(2.34)
Square of initial household wealth × 10^{12} (¢)	-0.026	0.17
	(0.054)	(0.23)
Constant	19.22*	2.806
	(10.76)	(16.02)
Observations	268	268
R-squared		
Joint Wald Test of Hypothesis (Prob>chi2)		
Initial wealth and square of wealth	0.47	0.74
Number of pid	237	237

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In the household labor allocation model, the percentage of household acreage in maize is used to control for the importance of maize to the household as a source of food or income. According to Table 6.5, the percentage of household acreage in maize has a significant negative effect on on-farm labor allocation at the 5% level while its square has a significant positive effect. At the means of the sample, the marginal effect of percentage of acreage in maize on on-farm labor allocation is positive as expected. As the percentage of household acreage in maize increases, they allocate more labor to maize per acre. Beyond 61%, the percentage of acreage in maize has a negative effect on on-farm labor allocation. In the case of non-farm labor allocation, the percentage of household acreage in maize is not statistically significant. The average percentage of household acreage in maize is about 73%.[30]

For on-farm labor allocation, the signs of the coefficient for negative health event and measure of ex ante yield risk are positive and negative, respectively, but neither is statistically significant. The negative sign of the effect of ex ante yield risk on on-farm labor allocation is in support of the negative effect of risk on input allocation and the traditional assumption that smallholder households are risk averse. However, the effect of ex ante yield risk on on-farm labor allocation is not significant at even the 10% level. Therefore the hypothesized effect of ex ante yield risk on on-farm labor allocation is not confirmed.

The situation is different for non-farm labor allocation which is negatively influenced by negative health events but positively by ex ante yield risk, albeit insignificantly. This finding indicates that the households in the sample do not necessarily increase their participation in the labor market and other non-farm activities in response to an increase in ex ante yield risk. This suggests households do

[30] Refer to Figure B.4 of Appendix B for the distribution of the percentage of household acreage in maize.

not consider the wage labor market and other income generating activities as less risky compared to farming. Since ex ante yield risk does not significantly affect non-farm labor, the hypothesis that non-farm labor responds positively to ex ante yield risk is not confirmed. Another possible explanation is that they cannot easily increase their off-farm employment due to limited market demand. In contrast to on-farm labor, the effect of negative health events experienced by the household on non-farm labor allocation is negative, likely reflecting loss of household labor supply to illness and the prioritization of on-farm work over off-farm employment.

In general, the statistical insignificance of the effect of yield risk and shocks on planting period labor allocation is consistent with the earlier finding that households have alternative mechanisms for dealing with yield risk and shocks. Therefore, household labor allocation does not respond radically to incidence of shocks and ex ante yield risk.

The village and seasonal dummies control for unobservable characteristics and other omitted variables. The effect of season 1 on on-farm labor allocation is negative and significant at the 1% level. Season 2 and all the village dummies have insignificant effects on on-farm labor. Non-farm labor is negatively influenced by the season 1 dummy variable and is significant at the 5% level. The remaining village and seasonal dummy variables do not significantly influence non-farm labor allocation.

The other household characteristics do not have significant effects on on-farm labor allocation intensity. The occupation of the household head has a positive effect on on-farm labor allocation as expected. Household heads who are farmers are expected to allocate more labor per acre than those who are not. This makes intuitive sense since heads who are farmers are more likely to devote more attention to crop production in order to guarantee good yields. The insignificant effect of occupation can be explained by the fact that 90% of the sample consist of maize farmers. As reported in Table 6.6, planting period exogenous income has a minute marginal effect on on-farm labor allocation. The remaining variables for household characteristics do not have significant effects on non-farm labor.

Table 6.6—Estimated Marginal Effects and Elasticities of Selected Variables on Ex ante Labor Allocation

	Marginal Effects		Elasticities	
Variable	On-farm	Non-farm	On-farm	Non-farm
Percentage of acreage in maize	5.349	8.890	0.052	0.086
Planting period income × 10,000 (¢)	-0.01	0.07	-0.006	0.033
Initial household wealth × 10,000(¢)	0.00	0.01	-0.002	0.013

Note: the above is based on the random effects estimates for the on-farm and non-farm labor allocation models.

To clarify the effect of initial household wealth on labor allocation in the planting period, I consider estimates of the marginal effect of wealth on labor followed by a test of hypothesis.[31] Initial household wealth does not significantly affect both non-farm and on-farm labor allocation. This is further confirmed by a test of hypothesis of the joint significance of initial wealth and its square. This suggests that initial wealth is not important in explaining household ex ante labor allocation.

Table 6.7 reports the estimates of the coefficients of the household labor allocation model for the preharvest period (ex post). The estimates of the marginal effects and elasticities for the planting period on-farm labor, planting period non-farm labor, percentage of acreage in maize, planting and preharvest period exogenous incomes are presented in Table 6.8. In the next few paragraphs, I discuss the results of the model for on-farm labor allocation followed by non-farm labor allocation.

[31] Refer to section G.2 of Appendix G for the test statistics of the Wald Test

Table 6.7—Household Labor Allocation Model for Preharvest Period

Variables	On-Farm Labor	Non-Farm Labor
Planting Period Labor Allocation		
Predicted planting period on-farm labor (days/acre)	1.318***	0.255
	(0.284)	(0.190)
Square of predicted planting period labor	-0.0102***	-0.00184
	(0.00318)	(0.00180)
Predicted planting period non-farm labor (days)	0.354***	-0.0247
	(0.0937)	(0.0275)
Square predicted planting period non-farm labor	-1.21e-05	5.45e-05
	(0.000195)	(5.31e-05)
Percentage of acreage in maize	-7.967	-3.009
	(14.05)	(11.52)
Square of percentage in acreage	4.831	3.129
	(11.44)	(10.79)
Idiosyncratic Shocks and Risk Measure		
Damage to stored crops in planting period	-2.173	-1.111
	(3.326)	(1.257)
Damage to other crops in planting period	-1.848	-3.294
	(3.188)	(2.422)
Negative health events in previous season	0.878	1.321
	(2.020)	(2.359)
Negative health events in planting period	-0.965	0.215
	(1.798)	(1.777)
Unexpected expenses in planting period	-1.660	-0.780
	(2.364)	(0.801)
Standard deviation of yield	-0.210	0.0424
	(0.177)	(0.133)
Village and Seasonal Dummies		
Darmang	-2.568	-0.231
	(2.344)	(1.892)
Pokrom	-4.636	-0.225
	(3.131)	(2.256)
Oboadaka	-0.374	2.023
	(2.494)	(1.556)
Season 1 (March 96 to July 97)	5.731*	0.339
	(3.113)	(1.172)
Season 2 (August 97 to January 98)	1.997	10.82***
	(2.895)	(1.978)
Household Characteristics		
Planting period income × 1,000,000 (¢)	-0.89	-0.21
	(1.34)	(0.72)
Preharvest period income × 1,000,000 (¢)	2.05	-2.30
	(4.97)	(1.56)
Square of planting period income × 10^{12}	0.19	-0.029
	(0.24)	(0.09)
Square of preharvest period income × 10^{12}	-1.12	0.70
	(1.67)	(0.54)
Occupation of household head	1.005	-2.207
	(2.091)	(1.910)
Education of household head	-1.569	2.687
	(3.073)	(1.953)
Age of household head	0.00275	0.0520
	(0.0602)	(0.0670)

Table 6.7 (Continued)

Variables	On-Farm Labor	Non-Farm Labor
Initial household wealth × 1,000,000 (¢)	-1.30*	0.26
	(0.74)	(0.36)
Square of initial household wealth × 10^{12}	65.1	-22.9
	(40.9)	(23.1)
Constant	9.651	-4.516
	(7.995)	(7.021)
Observations	268	268
R-squared		
Number of pid	237	237
Joint Wald Test of Hypothesis (Prob>chi2)		
Idiosyncratic Shocks	0.93	0.55
Initial wealth and square of wealth	0.08	0.46
Predicted planting period on-farm labor	0.00	0.36
Predicted preharvest period non-farm labor	0.00	0.58

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Referring to Table 6.8, predicted planting period on-farm labor has a positive marginal effect on on-farm labor. A Wald test of the joint significance of planting period on-farm labor and its square produces a test statistic with a p-value less than 0.01.[32] This confirms the hypothesis that planting period on-farm labor allocation has a positive influence on on-farm labor allocation in the preharvest period. Hence, when the household allocates labor in the preharvest period they take into account how much on-farm labor per acre they allocated during the planting period. This means farmers probably regard planting and preharvest period on-farm labor as compliments. The household has less flexibility with regards crop production than other non-farm income activities. Predicted non-farm labor has a significant positive effect at the 1% level but its square is negative and insignificant even at 10%.

Predicted planting period non-farm labor has a positive marginal effect (at the sample mean) on on-farm labor in the preharvest period. Based on the result of a Wald test of the joint significant of predicted planting period non-farm labor and its square, I

[32] Refer to A.2 of Appendix A for details of the results of the Wald test.

fail to reject the null hypothesis that predicted planting period non-farm labor has no influence on on-farm labor allocation in the preharvest period. The p-value of the test statistic is 0.55.[33]

When the household makes non-farm labor allocation decisions in the preharvest period, does not consider planting period labor allocation. Predicted on-farm labor allocation during the planting period does not significantly (even at the 10% level) affect non-farm labor allocation in the preharvest period. The coefficient for predicted planting period on-farm labor allocation is positive (0.255 days/acre) while its square is positive (-0.002 days/acre). At the mean of the sample, the marginal effect of predicted planting period on-farm labor is positive (Table 6.8). A joint test of significant is performed and the p-value of the Wald test statistic is 0.36.[34] This result rejects the hypothesis that planting period on-farm labor allocation influences preharvest period non-farm labor allocation. The estimated coefficients for predicted planting period non-farm labor and its square are not significantly greater than zero. At the mean of the sample, the marginal effect of planting period non-farm labor is negative. A Wald test of joint significance revealed that non-farm labor allocation and its square are insignificant even at the 10% level. This conclusion rejects the hypothesized positive marginal effect of planting period non-farm labor on preharvest period non-farm labor allocation.

From the on-farm labor allocation model (Table 6.7), the percentage of household acreage in maize does not have a significant effect on labor allocation in the preharvest period. As shown in Table 6.8, the marginal effect of the percentage of acreage in maize on preharvest on-farm labor allocation is negative for both on-farm and non-farm labor allocation. However, the sign of the marginal effect for non-farm

[33] Refer to section G.2 of Appendix G for details of the Wald tests.
[34] Refer to section G.2 of Appendix G for details of the Wald tests.

labor is opposite that of on-farm labor. This finding is contrary to what one would expect as crop production is an important source of income for the household.

The importance of idiosyncratic shocks for determining on-farm labor allocation is less than expected. None of the idiosyncratic shocks considered in the model has a significant effect on on-farm labor. They all negatively affect on-farm input allocation except for negative health events experienced by the household in the planting period. Damage to stored crops in the planting period has the strongest effect on on-farm labor in terms of magnitude. This indicates that damages to stored crops can have strong disincentive effects on labor allocation to crop production. However, it is difficult to tell what the potential effect of damage to specific crops in storage is likely to be. Predictably, ex post yield risk has a negative effect on labor allocation to crop production; however, it is not significant.

I fail to reject the null hypothesis that ex post yield risk has no effect on on-farm labor allocation. The negative relationship between ex post yield risk and on-farm labor allocation in the preharvest period reflects an aversion to yield risk. All the idiosyncratic shocks considered do not have a statistically significant effect on non-farm labor. They all negatively affect non-farm labor allocation except for negative health events in the planting period and previous season which positively affect non-farm labor. Damaged to other crops in the planting period have the largest coefficients in terms of magnitudes among all the shocks considered in the non-farm labor allocation model. The positive coefficient of negative health events experienced during the planting period is consistent with its negative effect on preharvest period on-farm labor.

The yield risk faced by the household in the preharvest period (ex post yield risk) has a positive but insignificant effect on preharvest non-farm labor allocation (Table 6.7). The effect of ex post yield risk on non-farm labor (0.042 days/acre) as opposed to on-farm labor (-0.21) weakly supports the assumption of risk averse behavior of farmers. This result suggests that the household regards participation in the labor market as less risky than crop production and therefore increases their non-farm labor allocation in response to an increase in ex post yield risk. This finding is consistent with the results of the planting period where yield risk has the same effect.

The statistical insignificance of the effect of idiosyncratic shocks and ex post yield risk on preharvest period labor allocation is consistence with the finding for the planting period. This confirms that households indeed have alternative measures for managing shocks and yield risk which does not involve labor allocation (both on-farm and non-farm).

Seasonality is important for both on-farm and non-farm labor allocation in the preharvest period. For on-farm labor allocation, the coefficient for season 1 is positive and significantly different from zero at 10% level. This finding is difficult to interpret since seasonality encompasses many characteristics including prices, access to important services, weather and events that can influence labor allocations. The village dummy variables considered in the model do not have significant effects on on-farm labor. For non-farm labor allocation, season 2 has a significant effect at the 1% level. Season 2 has a positive coefficient of 10.82 days per acre. Season 2 is the minor rainy season and therefore the household increases its participation in income-generating activities other than maize cultivation. For season 2, the household expects lower maize yields compared to season 1 and season 3; hence they decrease the attention they give to maize production.

In general, planting and preharvest period exogenous incomes do not play a significant role in explaining household on-farm labor decisions in the preharvest period. The coefficients for these variables are very low in magnitude. Planting and preharvest period exogenous incomes and their squares do not significantly affect on-farm labor allocation. The marginal effects of planting and preharvest period exogenous income at the mean of the sample are both positive, respectively. Based on the positive coefficient for the square of planting period exogenous income in the on-farm labor allocation model (Table 6.7), households with high levels of planting period exogenous incomes greater than a certain critical value have marginal effects estimates for planting period exogenous income which are positive. Similarly, the marginal estimates for preharvest period exogenous income become negative at high levels of preharvest period exogenous income. The marginal effects of planting and preharvest period exogenous income are positive at the mean of the sample.

Table 6.8—Estimated Marginal Effects and Elasticities of Selected Variables on Ex Post Labor Allocation

	Marginal Effects		Elasticities	
Variable	On-farm	Non-farm	On-farm	Non-farm
Predicted planting period on-farm labor	1.20	0.23	0.09	0.02
Predicted planting period non-farm labor	0.35	-0.02	0.03	0.00
Percentage of acreage in maize	-0.93	1.55	-0.01	0.01
Planting period income × 1,000 (¢)	0.14	0.00	0.69	0.00
Preharvest period income × 1,000,000 (¢)	0.00	0.00	0.00	0.00
Initial household wealth × 1,000 (¢)	0.22	0.00	0.00	0.00

To analyze and clarify the effect of initial household wealth on labor allocation in the preharvest period, I use the estimates of marginal effects in Table 6.8 and joint tests of hypotheses. Initial wealth significantly influences on-farm labor allocation at the 1% level while its square insignificantly influences on-farm labor allocation. The marginal effect of initial wealth at the mean is positive but very low. A test of the joint significance of initial wealth and its square is performed; the p-value of Wald test[35] statistic is 0.08 and therefore initial wealth and its quadratic term are significant at the 10% level. The square of initial wealth has a positive coefficient. Therefore at low

[35] Refer to section G.2.12 of Appendix G for details of the results.

wealth levels, initial household wealth has a negative effect on on-farm labor allocation. The negative marginal effect of initial wealth on on-farm labor at low levels of initial might be as a result of poor households reducing their exposure to yield risk thereby protecting their wealth. Initial wealth and its square do not have significant influence on non-farm labor. The estimated marginal effect of initial wealth on non-farm labor is very close to zero at the mean. A Wald test of the joint significance resulted in a p-value of 0.46. Therefore, I fail to reject the null hypothesis that initial household wealth and its square jointly influence preharvest period non-farm labor allocation.

CHAPTER 7

CONCLUSIONS, CONTRIBUTIONS, AND RECOMMENDATIONS

7.1 Conclusions

There have been numerous studies examining the role of shocks in household production decisions. However, most of theses studies have focused on covariate shocks at the expense of idiosyncratic shocks. In this thesis, I explore the role of idiosyncratic shocks and risk on smallholder labor allocation decisions using a two period expected utility model. Labor allocation is analyzed taking into account the sequential/dynamic nature of crop production from an ex ante and ex post perspective. Using a Just-Pope framework, I estimate the effect of idiosyncratic shocks on yield and conditional yield variance. The data were obtained from a panel study conducted from November 1996 to August 1998 in southern Ghana.[36]

The marginal physical product of planting period labor is greater (but not significantly) than that of the preharvest period. The elasticities of planting and preharvest period labor are between 0 and 1 which indicates maize production is taking place in stage 2. Hence, households have the ability to allocate labor optimally. This may be tendered as evidence that households know how to grow maize properly to an extent. The occupation of the household head has a positive effect on maize yields; households with heads who are farmers enjoy higher maize yields as compared to households whose heads are not. The initial wealth of the household does not have an important effect on yield and has an estimated positive marginal physical product which is minute compared to mean household maize yield. Therefore *ceteris paribus* richer households do not necessarily obtain higher maize yields than poorer ones. In

[36] Refer to A.1 of Appendix A for source and description of data.

assessing the impact of idiosyncratic shocks on maize yield, it is important to consider the type and timing of shocks. The occurrence of unexpected expenses and damage to stored crops in the planting period has a prominent negative effect on maize yields. From the above discussions, it is evident that idiosyncratic shocks decrease the productivity of labor allocated to maize production by the household.

The results in this thesis strongly suggest that among all the idiosyncratic shocks considered only negative health events in the previous season contribute to the riskiness of maize yields. Therefore, the main sources of yield risk are planting period on-farm labor allocation, village effects, seasonality and negative health events from the previous season which are all risk-increasing. Planting and preharvest period on-farm labor have a negative interaction and their marginal effect is positive (at the mean of the sample). According to the estimate of the elasticity of planting period on-farm labor, yield risk is inelastic to changes in planting period on-farm labor allocation. Another source of yield risk is initial household wealth but the marginal risk effect estimate of initial wealth is very small. The effect of initial wealth on risk is concave and inelastic; therefore only household's with extremely high wealth values can benefit from the risk-decreasing effect of wealth.

The effects of idiosyncratic shocks on labor allocations are analyzed using an ex ante and ex post labor allocation model. In the planting period, seasonal effects help explain both on-farm and non-farm labor allocation. Ex post on-farm labor allocation is positively influenced by on-farm and non-farm labor allocation during the planting period; estimates of their marginal effects is positive (Table 6.8). Thus the household considers planting period labor allocation when making on-farm allocation decisions in the preharvest period. The positive marginal effect of planting period on-farm labor allocation means the household treats planting period on-farm labor allocation and preharvest period on-farm labor allocation as compliments. The household also considers planting period non-farm labor allocation when making ex post on-farm labor allocation. None of the idiosyncratic shocks considered for the preharvest period have a significant influence on ex post on-farm labor allocation. They all have negative effects except for negative health events in the previous season which has a positive effect. Initial wealth has a very small marginal effect on ex post on-farm labor allocation. As a result, it does not play a significant role in household on-farm labor allocation behavior in the preharvest period.

Planting period on-farm and idiosyncratic shocks do not help explain ex post non-farm labor allocation. This is probably because planting period labor allocation is not factored into decision making about ex post non-farm labor allocation. Similar to on-farm labor allocation, none of the idiosyncratic shocks considered for the preharvest period are important variables for explaining ex post non-farm labor allocation. They all negatively influence ex post non-farm labor allocation except for negative health events. The marginal effect of initial wealth on ex post non-farm labor allocation at the sample mean is negative but very close to zero. As in the planting period, there is evidence of seasonal effects on ex post non-farm labor allocation.

For both the planting and preharvest periods, the negative effect of yield risk on on-farm labor allocation and its positive effect on non-farm labor allocation is partially in support of the assumption of household aversion to risk. Idiosyncratic shocks do not have a clear effect on yield risk and labor allocation; however, damage to stored crops and unexpected expenses in the planting period have strong effects on mean plot-level yields. This suggests the adoption of reasonably effective mechanisms that sufficiently cushion household against the negative effects of idiosyncratic shocks. Therefore households do not drastically change their labor allocation patterns in response to shocks and yield risk. This is consistent with qualitative findings based on discussions I had with Akwapim farmers in summer 2009. The significant negative effects of damage to stored crops and unexpected expenses in the planting period indicates that mechanisms adopted by households for managing idiosyncratic shocks are not effective for shocks that decrease the cash budget of the household.

Initial household wealth does not significantly influence estimated mean yields but is strongly associated with increased yield risk and is negatively but weakly associated with labor allocation per acre. Hence wealthier households contrary to expectation do not choose higher risk/higher return maize production technology. This is probably because wealthier farmers are able to engage in activities that distract them from maize production leading to higher yield risk. This finding is not consistent with a self-insurance hypothesis.

7.2 Summary of Contributions

In this thesis, I use a two period expected utility model to analyze labor allocation taking into account both the incidence of shocks and the dynamic nature of agricultural production while incorporating a measure of risk faced by the household. Therefore, I examine the impact of idiosyncratic shocks already experienced by the household and yield risk perception during the season on labor allocation. The household's yield risk perception is examined by introducing the concept of ex ante and ex post yield risk (Holt *et al*., 1992; Sandmo, 1970) into the analysis of on-farm labor allocation.

Past studies have used estimates for analyzing the effect of idiosyncratic shocks on household labor allocation behavior (e.g. Kochar, 1994). In this thesis, I use direct measures of household-specific idiosyncratic shocks. Households are asked directly about idiosyncratic shocks.

7.3 Recommendations

In spite of the drastic negative effect of certain types of idiosyncratic shocks on maize yield, households ex ante and ex post on-farm labor allocation do not respond to them in terms of their on-farm labor allocation. Idiosyncratic shocks are only important for ex post non-farm labor allocation. The estimated marginal physical product for planting period labor is greater than zero. Thus on-farm labor is below the yield maximizing level. They also sacrifice the risk-decreasing effect resulting from the negative interaction between planting and preharvest period on-farm labor allocation. The role played by wealth in explaining household production decisions is at best marginal as it has a very small effect on productivity, labor allocation and yield risk. However, seasonal and village effects have strong effects. Households with heads who are farmers enjoy higher yields compared to those whose heads are not.

The above discussions have implications for designing policies to help rural households in Akwapim South cope with the occurrence of idiosyncratic shocks and their concomitant risk. Therefore policy-makers should focus on designing extension programs to help farm households improve their labor productivity without necessarily making crop production riskier. The effects of location and time on labor productivity should also be taken into account. As evidenced by the results, maize production in Darmang is riskier than in the other three villages; however, maize yields in Darmang are higher than the other villages.

Based on the findings of this thesis, I also recommend that further research be carried out into understanding mechanisms smallholder farm households use for managing idiosyncratic shocks and yield risk. Households do not radically change their labor allocation patterns in response to the incidence of idiosyncratic shocks and yield risk.

APPENDIX A

SURVEY AND VARIABLE DESCRIPTION

A.1 Data Collection

Data were collected from four villages in southern Ghana—Darmang, Pokrom, Konkonuru and Oboadaka—from November 1996 to August 1998. The survey was conducted by Christopher Udry of the Department of Economics, Yale University and Markus Goldstein of the Department of Agricultural and Resource Economics, University of California, Berkeley. The data can be found at Christopher Udry's website: http://www.econ.yale.edu/~cru2//ghanadata.html

Round: This refers to a data collection period. Respondents are asked questions about events that occurred over a given period e.g., past x months. For example, "how many bags of maize did you harvest over the last 2 months?" Below is the schedule for the interviews:

Round 1:11/25/1996

Round 2:1/27/1997

Round 3:3/3/1997

Round 4:4/14/1997

Round 5:6/2/1997

Round 6:7/7/1997

Round 7:8/18/1997

Round 8:9/29/1997

Round 9:12/2/1997

Round 10:1/20/1998

Round 11:3/16/1998

Round 12:4/27/1998

Round 13:5/25/1998

Round 14:6/29/1998

Round 15:8/3/1998

In round 1, respondents answered questions about household membership. In round 2 questions were asked about events that occurred between the current interview (1/27/1997) and the last interview (11/25/1996). The same pattern was repeated for the remaining rounds.

A.2 Variable Description

Season: There are approximately 2 maize seasons in a single year. This variable refers to the season in which an activity took place.

SEASON1 (planting period): March 1997

SEASON1 (preharvest period): April to June 1997

SEASON2 (planting period): August 1997

SEASON2 (preharvest period): September to December 1997

SEASON3 (planting period): March 1998

SEASON3 (preharvest period): April to June 1998

This is to some extent similar to the major and minor maize seasons in Akwapim South. I learned this during my face-to-face interviews with farmers.

Village 1: This is a dummy variable which has a value of 1 if the household of the respondent is located in Darmang and 0 if otherwise.

Village 2: This is a dummy variable which has a value of 1 if the household of the respondent is located in Pokrom and 0 if otherwise.

Village 3: This is a dummy variable which has a value of 1 if the household of the respondent is located in Oboadaka and 0 if otherwise.

Village 4: This is a dummy variable which has a value of 1 if the household of the respondent is located in Konkonuru and 0 if otherwise.

Damage to stored crop in previous preharvest and harvest period: this refers to damage to crops in storage experienced by the household in the preharvest and harvest period of the previous season. It is a dummy variable which takes a value of 1 if the household experienced this type of shock and 0 if otherwise.

Damage to stored crops in planting: this refers to damage to crops in storage experienced by the household in the planting period of the current season. It is a dummy variable which takes a value of 1 if the household experienced this type of shock and 0 if otherwise.

Negative health events in previous preharvest and harvest period: this refers to negative health events experience by member(s) of the household in the planting period of the previous season. It is a dummy variable which takes a value of 1 if the household experienced this type of shock and 0 if otherwise.

Negative health events in planting period: this refers to negative health events experienced by member(s) of the household in the planting period of the planting season. It is a dummy variable which takes a value of 1 if the household experienced this type of shock and 0 if otherwise.

Unexpected expenses in preharvest and harvest period: this refers to unexpected expenses experienced by members of the household in the preharvest and harvest periods of the previous season. Examples of unexpected expenses are funeral expenses, increase in cost of farming tools and breakdown of productive assets. It is a dummy variable which takes a value of 1 if this type of shock is experienced by the household and 0 if otherwise.

Unexpected expenses in planting period: this refers to unexpected expenses experienced by members of the household in the planting period of the previous season. Examples of unexpected expenses are funeral expenses, and breakdown of productive assets. It is a dummy variable which takes a value of 1 if this type of shock is experienced by the household and 0 if otherwise.

Initial wealth (¢): this is the wealth of the household in 1997/98 Ghanaian currency[37] at the beginning of the season or before the planting period begins. Wealth is defined as the sum of the value of food and farm output in storage, planting materials, farm equipment, other durable goods, livestock, jewelry, cloth, tradable goods, foreign exchange, amount spent on buildings, susufunds,[38] and bank balances net of loans given to and received from external sources.

Age: this variable refers to the age in years of the household head.

Education: this is a dummy variable which take a value of 1 if the household has had some schooling and 0 if otherwise.

Planting period exogenous income (¢): this refers to income in1997/98 Ghanaian currency earned by the household from sources other than maize during the planting period of the season. This is the total value of sales for crops other than maize (value#) for the planting period of each season. For example, the planting period exogenous income for season 1 is given by the sum of the value of sales for round 3 and 4. I used non-maize income to represent exogenous income because most household did not report other sources of income.

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[37] The Ghanaian currency was redenominated in 2007; this constituted the removal of four zeros.

[38] A susufund is a savings fund managed by individuals called susu collectors. Susu collectors manage funds for several people. They visit their clients to collect fixed amounts at regular time intervals e.g. weekly, biweekly and monthly. This system is entirely based on trust and clients do not earn interest.

Preharvest period exogenous income (¢): this refers to income in1997/98 Ghanaian currency earned by the household from sources other than maize during the preharvest period of the season. This is the total value of sales for crops other than maize (value#) for the preharvest period of each season. For example, the planting period exogenous income for season 1 is given by the sum of the value of sales for round 5, 6 and 7. I used non-maize income to represent exogenous income because most household did not report other sources of income.

Percentage of acreage in maize: this is the percentage of total household acreage occupied by maize. This the sum of all household maize acreage (acre) divided by total household acreage (totacre) for the current period.

Acre: this is the household's maize acreage.

Planting period labor (days/acre): this is the number of days of labor allocated per acre by the household during the planting period of the current season. For example, the planting period labor for season 1 is given by the sum of the number of days of labor allocated during round 3 (days_lab3).

Preharvest period (days/acre): this is the number of days of labor allocated per acre by the household during the preharvest period of the current season. For example, the preharvest period labor for season 1 is given by the sum of the number of days of labor allocated by the household during round 4 (days_lab4) and 5 (days_lab5).

Planting period non-farm labor (days/acre): this is the number of days of labor allocated to activities other than maize cultivation by the household during the planting period of the current season. This consists of the sum of days of labor allocated to other businesses (hhlab_nf1) and number of days worked by head and spouse (totdays) for other people.

Preharvest period non-farm labor (days/acre): this is the number of days of labor allocated to activities other than maize cultivation by the household during the preharvest period of the current season. This consists of the sum of days of labor allocated to other businesses (hhlab_nf2) and number of days worked by head and spouse (totdays2) for other people.

APPENDIX B

DESCRIPTIVE STATISTICS AND PLOTS

Table B.1—Descriptive Statistics for Important Variables

Variable	Mean	SD
Plot Level Characteristics		
Maize yield (kg/acre)	75.3	103.61
Planting labor (days/acre)	5.9	12.33
Preharvest labor (days/acre)	12.6	17.01
Acreage	5.1	7.19
Percentage of acreage in maize	0.7	0.36
Plot Level Shocks		
Damage to maize in previous harvest and preharvest period	0.00	
Damage to maize in planting period	1.12	
Damage to other crops in previous harvest and preharvest period	1.12	
Damage to other crops in planting period	7.43	
Household Level Shocks		
Damage to stored crop in previous harvest and preharvest period	0.96	
Damage to stored crop in planting period	6.73	
Negative health events in previous preharvest and harvest period	18.75	
Negative health event in previous planting period	31.25	
Unexpected expenses in previous harvest and preharvest period	0	
Unexpected expenses in planting period	12.98	
Village Dummies (1 if yes, 0 otherwise)		
Darmang	34.6	
Pokrom	6.7	
Oboadaka	40.2	
Konkonuru	18.6	
Season Dummies (1 if yes, 0 otherwise)		
Season 1 (March 96 to July 97)	52.4	
Season 2 (August 97 to January 98)	27.9	
Season 3 (March 98 to July 98)	19.7	
Household Characteristics		
Initial wealth	1690000	2920000
Occupation of household head	88.9	
Age of household head	43.4	13.31
Education status of household head	86.6	
Planting period non-farm labor (days)	7.5	19.22
Preharvest period non-farm labor (days)	6.8	16.38
Planting period farm income (¢)	371000	1190000
Preharvest period farm income (¢)	222000	603000
Expected preharvest farm income (¢)	441000	1520000
Estimated Risk Measures (standard deviation)		
SD of maize yield in planting period	17.14	6.25
SD of maize yield in preharvest period	14.65	5.53

Table B.2—Descriptive Statistics for Important Variables

	Coefficient of Variation (%)		
Variable	Season 1	Season 2	Season 3
Maize yield (kg/acre)	147.94	74.16	106.97
Planting labor (days/acre)	204.44	169.97	102.02
Preharvest labor (days/acre)	117.15	120.33	145.00
Acreage	143.01	142.66	102.02

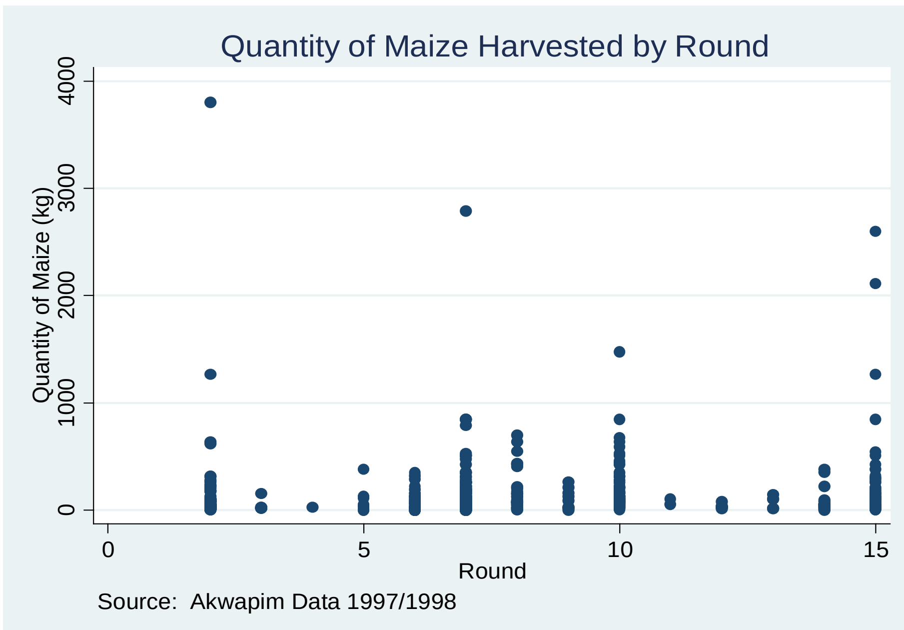

Figure B.1—Quantity of Maize Harvested by Round

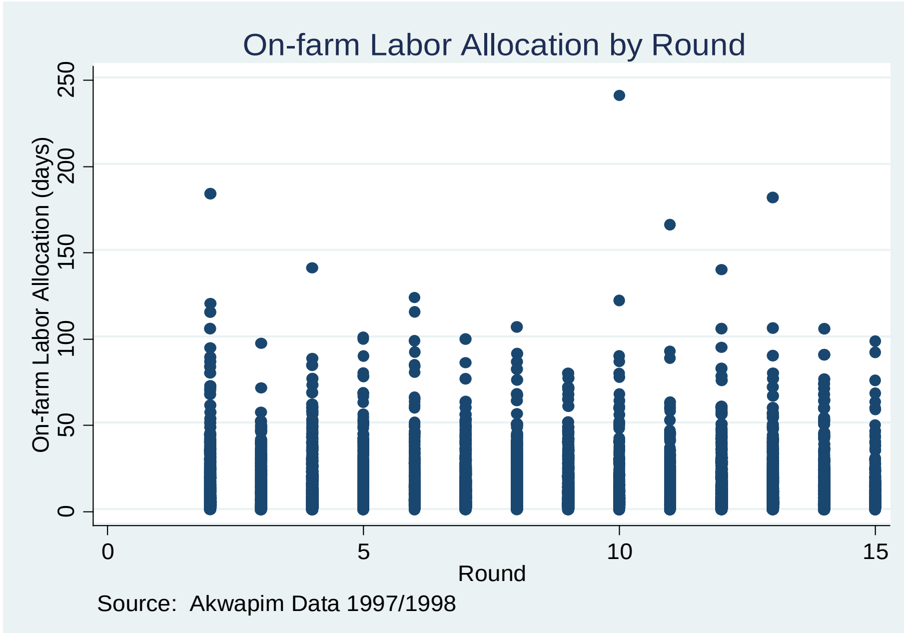

Figure B.2—On-farm Labor Allocation by Round

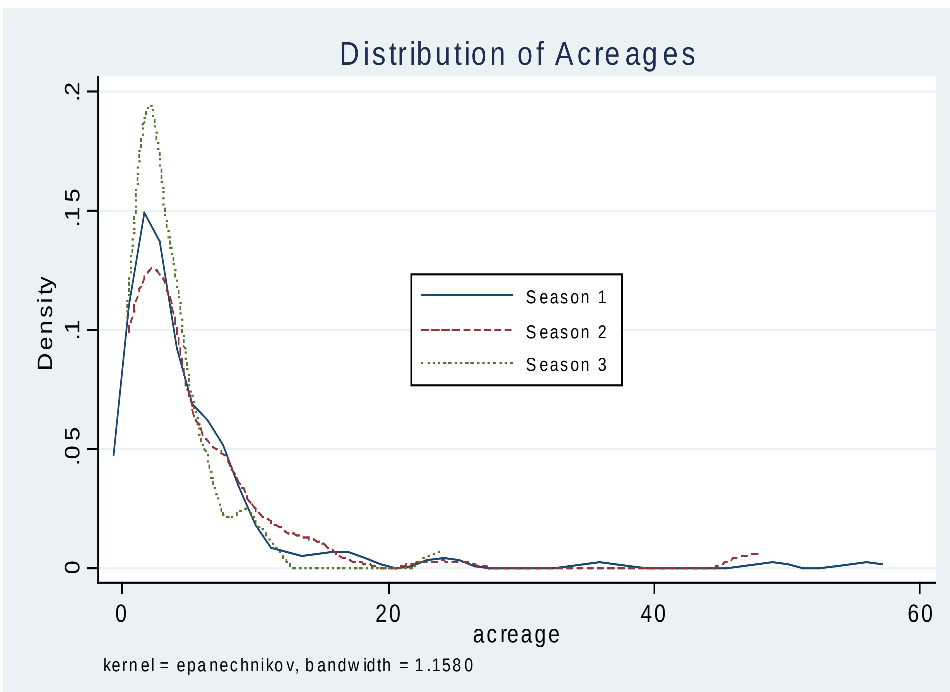

Figure B.3—Distribution of Household Acreage

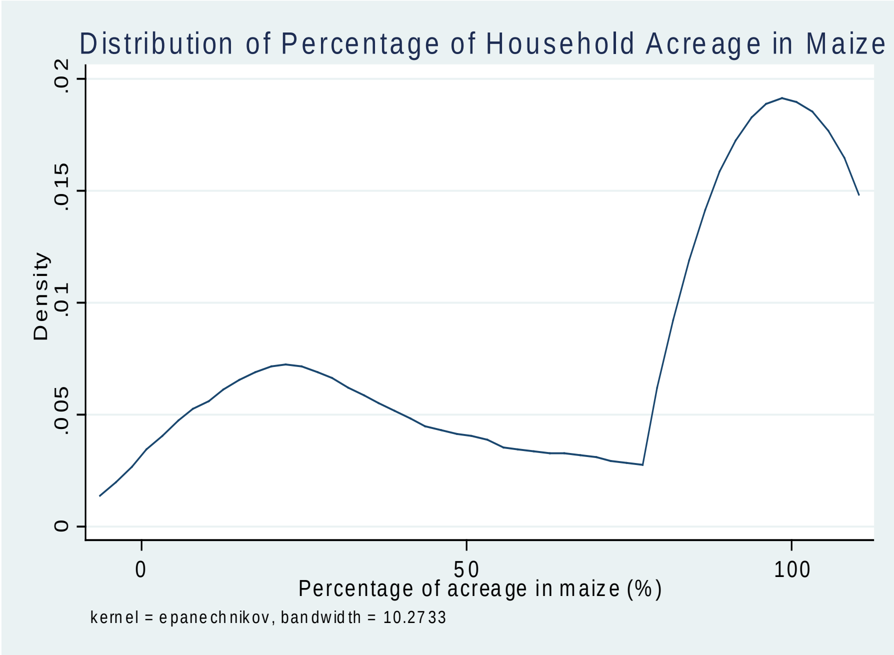

Figure B.4—Distribution of Household Acreage in Maize

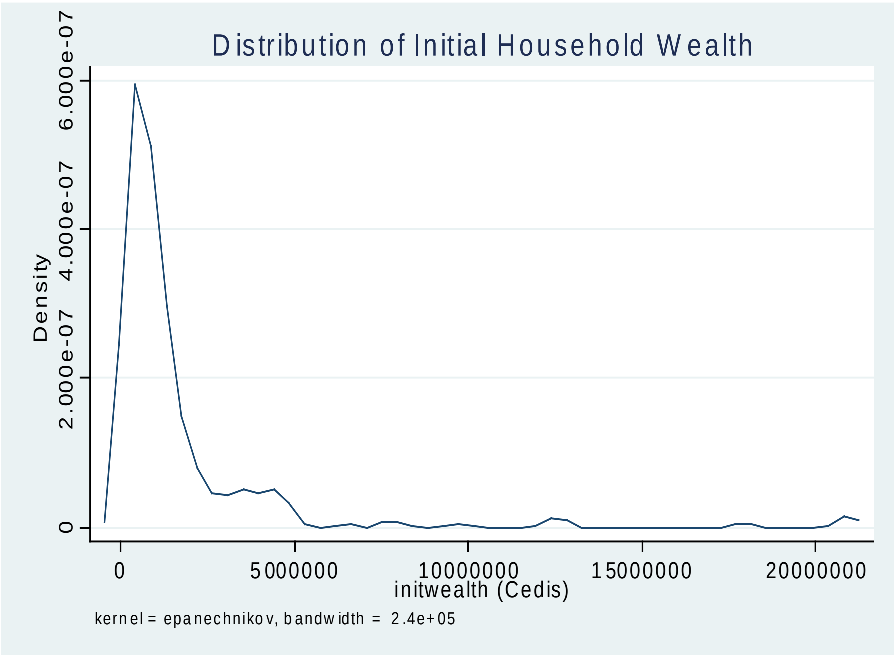

Figure B.5—Distribution of Initial Household Wealth

APPENDIX C

DIAGNOSTIC PLOTS OF RESIDUALS AGAINST LABOR

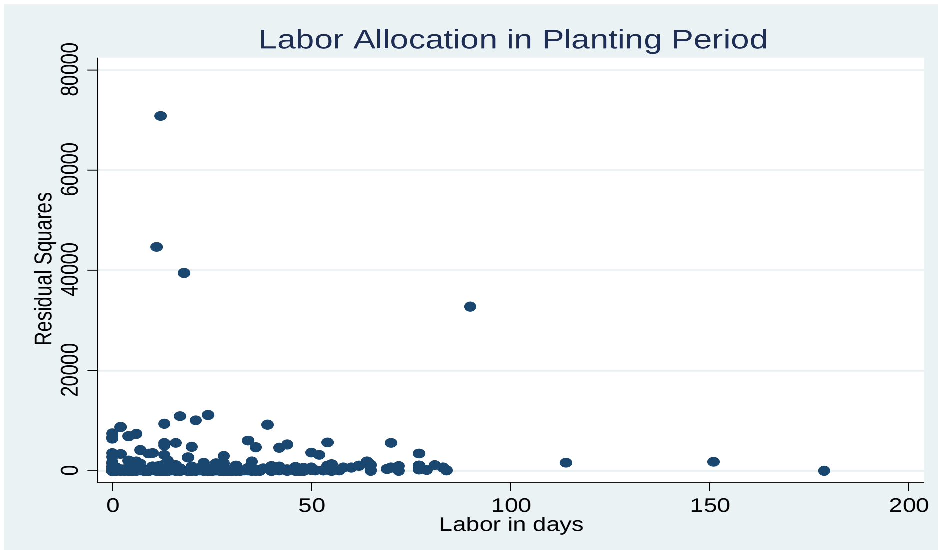

Figure C.1—Household Labor Allocation in Planting Period

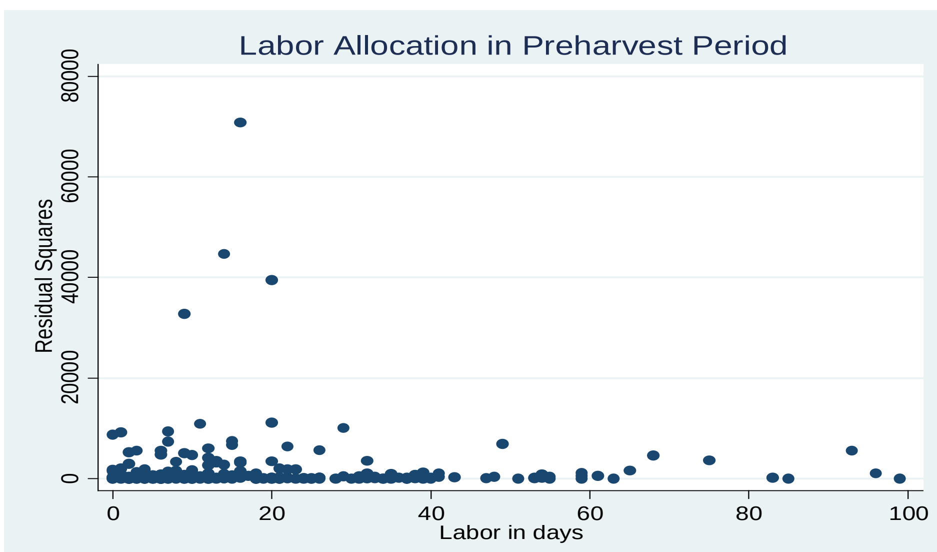

Figure C.2—Household Labor Allocation in Preharvest Period

APPENDIX D

HETEROSCEDASTICITY CORRECTION

D.1 Iterative Procedure for Heteroscedasticity Correction

The purpose of the iteration is to obtain correct standard errors for the parameters of the yield function. The iterative regression constitutes the following steps:

1. Maize yield is regressed on on-farm inputs and relevant household covariates. The standard errors of the coefficients are saved.
2. Residuals predicted from the first regression are squared.
3. The squared residuals are regressed on on-farm inputs and linear predictions are generated.
4. The square root of the absolute value of the linear predictions is taken. This is used to correct for heteroscedasticity by dividing all the variables of the regression (both dependent and independent) by it. The new set of variables is used to update the old ones.
5. A regression using the corrected variables in step 4 is performed. The standard errors of the coefficients are saved.
6. The standard errors of the coefficients of the regression in step 5 are compared to those of the regression in step 1. If the magnitude of the difference is greater than **0.05**, steps 1-5 are repeated. The steps are repeated until the magnitude of the difference is less than **0.05** which suggest convergence of the standard errors.

The iterative correction procedure is further illustrated in the equations below.

Consider a regression equation with heteroscedasticity:

$$y\sqrt{h(x_i)} = \beta_0\sqrt{h(x_i)} + \beta x_i\sqrt{h(x_i)} + \varepsilon_i\sqrt{h(x_i)}$$

The variance of random errors $u_i = \varepsilon_i\sqrt{h(x_i)}$ can be expressed as:

$$Var\left(\varepsilon_i\sqrt{h(x_i)}\right) = E\left(\varepsilon_i^2 h(x_i)\right) = \sigma^2 h(x_i)$$

In a weighted least square regression, where the source of heteroscedasticity is known, we can estimate $h(x_i)$ using an approximation $\hat{h}^n(x_i)$ which denotes the *nth estimation* of $h(x_i)$.

Therefore, if $\hat{h}^1(x_i) \approx h(x_i)$

$$\frac{y\sqrt{h(x_i)}}{\sqrt{\hat{h}^1(x_i)}} = \beta_0\frac{\sqrt{h(x_i)}}{\sqrt{\hat{h}^1(x_i)}} + \beta x_i\frac{\sqrt{h(x_i)}}{\sqrt{\hat{h}^1(x_i)}} + \varepsilon_i\frac{\sqrt{h(x_i)}}{\sqrt{\hat{h}^1(x_i)}}$$

$$\Rightarrow Var\left(\varepsilon_i\frac{\sqrt{h(x_i)}}{\sqrt{\hat{h}^1(x_i)}}\right) = E\left(\varepsilon_i^2\frac{h(x_i)}{\hat{h}^1(x_i)}\right) \approx \sigma^2$$

If we can estimate $\frac{h(x_i)}{\hat{h}^1(x_i)}$ such that $\frac{h(x_i)}{\hat{h}^1(x_i)} \approx \hat{h}^2(x_i)$

Then

$$\frac{h(x_i)}{\hat{h}^1(x_i)} - \hat{h}^2(x_i) \approx 0 \Rightarrow \frac{h(x_i)}{\hat{h}^1(x_i)\hat{h}^2(x_i)} - \hat{h}^3(x_i) \approx 0 \ldots \Rightarrow \frac{h(x_i)}{\hat{h}^1(x_i)\hat{h}^2(x_i)\ldots\hat{h}^{n-1}(x_i)} - \hat{h}^n(x_i) \approx 0$$

If $n \to \infty$ $\qquad \frac{h(x_i)}{\hat{h}^1(x_i)\hat{h}^2(x_i)\ldots\hat{h}^{n-1}(x_i)\hat{h}^n(x_i)} = 1$

From the above shows that we can solve the problem of heteroscedasticity by repeating WLS until the estimated variance of error terms $u_i = \varepsilon_i\sqrt{h(x_i)}$ converges.

D.2 Iterative Heteroscedasticity Correction

Table D.1—Final Regression for Iterative Heteroscedasticity Correction

Variables	Random Effects	Fixed Effects
Planting period labor	0.191**	0.245
	(0.0819)	(0.360)
Square of planting period labor	-0.00392*	-0.00927
	(0.00209)	(0.00808)
Preharvest period labor	0.0324	1.008*
	(0.0400)	(0.498)
Square of preharvest period labor	-0.000713	-0.0257**
	(0.000659)	(0.0120)
Planting labor × preharvest labor	0.00337	
	(0.00300)	
Village and Seasonal Dummies		
Darmang	4.898*	
	(2.615)	
Pokrom	-0.988	
	(0.971)	
Oboadaka	0.166	
	(0.617)	
Season 1 (March 96 to July 97)	-7.692**	6.645
	(3.649)	(5.326)
Season 2 (August 97 to January 98)	-9.077**	2.902
	(3.839)	(4.874)
Idiosyncratic Shocks (Dummy Variables)		
Damage to stored crop in previous harvest and preharvest	-10.31**	8.871
	(4.534)	(13.13)
Damage to stored crop in planting period	-0.120	9.711
	(1.030)	(7.253)
Negative health events in previous harvest and preharvest period	-0.327	1.802
	(0.506)	(3.327)
Negative health events in planting period	-0.566	-6.932*
	(0.591)	(3.594)
Unexpected expenses in planting period	1.009	-1.765
	(1.417)	(5.501)
Household Characteristics		
Occupation (1 if household head is farmer, 0 if otherwise)	-0.190	
	(2.813)	
Education (1 if household head had some schooling, 0 if otherwise)	0.0206	
	(0.441)	
Age of household head	0.305	
	(0.188)	
Square of age of household head	-0.00338*	
	(0.00188)	
Initial wealth	9.73e-07	-2.13e-06
	(8.17e-07)	(2.11e-06)
Square of initial wealth × 1000	-4.96e-11	1.61e-10
	(3.79e-11)	(1.99e-10)
Constant	0.579*	-0.225
	(0.318)	(0.540)

Table D.1 (Continued)

	Random Effects	Fixed Effects
Observations	269	269
R-squared		0.332
Number of pid	238	238

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

APPENDIX E

ESTIMATION OF EX ANTE AND EX POST YIELD RISK

Ex ante and ex post yield risk are estimated using pooled seasonal observations in order to take advantage of identification resulting from inter-seasonal, intra-household, plot-level, and cross-sectional variations among maize plots. Using a Just-Pope specification, we can estimate the season-plot-specific yield risk faced by each household. However, due to the simultaneity between on-farm labor allocation and yield risk, and the fact that yield risk is not observed by the household, yield risk is estimated using initial household wealth, past idiosyncratic shocks, household, seasonal, and village characteristics. Ex ante and ex post yield risk are estimated similarly with the only difference been in terms of idiosyncratic shocks already experienced by the household. Referring to (33) and (34), the only difference is idiosyncratic shocks (s_1) experienced by the household in the planting period of the current season.

I assume that the first two moments of yield are functions of initial household wealth, past idiosyncratic shocks, household, seasonal, and village characteristics. Using the Just-Pope method described in section 5.2, ex ante yield risk can be estimated sequentially in the following steps:

1. I estimate the yield function by regressing yield on initial household wealth, past idiosyncratic shocks, household, seasonal, and village characteristics (see Table E.1**)**.
2. I use the estimates from the regression in step 1 to generate residuals. Each plot will have a different residual.

3. I regress the square of the residuals on all the independent variables used in step 1 (see Table E.3**)**.
4. I use the estimates of the regression in step 2 to generate linear predictions. These linear predictions represent the ex ante yield risk faced by the household for each plot.

The above steps are repeated for estimating ex post yield risk with an additional independent variable s_1. Therefore, the household determine ex post yield risk by updating its knowledge of ex ante yield risk.

Table E.1—Estimation of Household Expected Yield in the Planting Period

Variables	Random Effects	Fixed Effects
Village and Seasonal Dummies		
Darmang	-39.84*	
	(20.59)	
Pokrom	-46.31	
	(30.63)	
Oboadaka	0.116	
	(19.22)	
Season 1 (March 96 to July 97)	14.34	20.84
	(11.47)	(15.22)
Season 2 (August 97 to January 98)	1.371	9.316
	(13.92)	(18.12)
Negative health events in previous harvest and preharvest period	11.16	-9.581
	(12.32)	(15.69)
Household Characteristics		
Occupation (1 if head is farmer, 0 if otherwise)	-24.00	
	(23.45)	
Education (1 if head had some schooling, 0 if otherwise)	14.78	
	(24.85)	
Age of household head	-5.221	
	(3.751)	
Square of age of household head	0.0418	
	(0.0392)	
Initial wealth	1.47e-05***	-9.09e-06
	(5.63e-06)	(1.54e-05)
Square of initial wealth × 1000	-6.71e-10**	7.68e-10
	(3.20e-10)	(1.24e-09)
Constant	217.7**	70.17***
	(88.40)	(20.36)
Observations	269	269
R-squared		0.138
Number of pid	238	238

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table E.2—Estimation of Household Expected Yield in the Preharvest Period

Variables	Random Effects	Fixed Effects
Village and Seasonal Dummies		
Darmang	-40.66**	
	(20.68)	
Pokrom	-56.46*	
	(31.00)	
Oboadaka	-4.675	
	(19.52)	
Season 1 (March 96 to July 97)	-11.51	-15.76
	(16.62)	(21.76)
Season 2 (August 97 to January 98)	-24.56	-23.90
	(18.25)	(23.21)
Idiosyncratic Shocks (Dummy Variables)		
Damage to stored crops in planting period	14.01	-9.448
	(29.13)	(58.64)
Damage to other crops in planting period	-8.216	0.246
	(18.63)	(27.85)
Negative health events in previous preharvest and harvest period	14.80	1.572
	(12.09)	(16.14)
Negative health events in planting period	4.897	-4.205
	(11.16)	(15.65)
Unexpected expenses in planting period	-56.47***	-80.02**
	(21.06)	(31.56)
Household Characteristics		
Occupation (1 if head is farmer, 0 if otherwise)	-23.12	
	(23.74)	
Education (1 if head had some schooling, 0 if otherwise)	19.56	
	(25.30)	
Age of household head	-5.126	
	(3.782)	
Square of age of household head	0.0401	
	(0.0395)	
Initial wealth	1.67e-05***	-2.56e-06
	(5.81e-06)	(1.66e-05)
Square of initial wealth × 1000	-8.19e-10**	4.51e-10
	(3.29e-10)	(1.24e-09)
Constant	238.5***	100.1***
	(89.22)	(24.88)
Observations	269	269
R-squared		0.378
Number of pid	238	238

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table E.3—Estimation of Household Conditional Yield Variance for Planting Period

Variables	Random Effects	Fixed Effects
Village and Seasonal Dummies		
Darmang	106.5	
	(176.1)	
Pokrom	-191.0*	
	(105.1)	
Oboadaka	-7.056	
	(108.9)	
Season 1 (March 96 to July 97)	18.53	-78.31
	(116.9)	(78.02)
Season 2 (August 97 to January 98)	-205.0	-326.0
	(139.5)	(307.2)
Negative health events in previous harvest and preharvest period	215.0	56.67
	(207.0)	(85.62)
Household Characteristics		
Occupation (1 if head is farmer, 0 if otherwise)	102.0	
	(189.0)	
Education (1 if head had some schooling, 0 if otherwise)	107.2	
	(136.4)	
Age of household head	-44.30	
	(30.71)	
Square of age of household head	0.376	
	(0.294)	
Initial wealth	0.000145***	1.13e-05
	(5.25e-05)	(6.54e-05)
Square of initial wealth × 1000	-7.59e-09***	-6.46e-10
	(2.63e-09)	(4.86e-09)
Constant	1105	242.8*
	(747.0)	(134.8)
Observations	269	269
R-squared		0.075
Number of pid	238	238

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table E.4—Estimation of Household Conditional Yield Variance for Preharvest Period

Variables	Random Effects	Fixed Effects
Village and Seasonal Dummies		
Darmang	77.85	
	(136.9)	
Pokrom	-157.5*	
	(81.19)	
Oboadaka	6.186	
	(80.22)	
Season 1 (March 96 to July 97)	-9.927	147.1
	(86.02)	(140.9)
Season 2 (August 97 to January 98)	-185.1	36.35
	(120.2)	(62.68)
Idiosyncratic Shocks (Dummy Variables)		
Damage to stored crops in planting period	-36.88	397.9
	(105.7)	(364.3)
Damage to other crops in planting period	-46.03	170.2
	(101.5)	(170.8)
Negative health events in previous preharvest and harvest period	216.4	99.10
	(147.7)	(104.1)
Negative health events in planting period	69.30	-217.5
	(114.3)	(197.3)
Unexpected expenses in planting period	-108.5	70.72
	(132.5)	(114.4)
Household Characteristics		
Occupation (1 if head is farmer, 0 if otherwise)	103.7	
	(141.1)	
Education (1 if head had some schooling, 0 if otherwise)	69.75	
	(90.62)	
Age of household head	-36.26	
	(26.02)	
Square of age of household head	0.309	
	(0.263)	
Initial wealth	9.35e-05***	-0.000159
	(3.09e-05)	(0.000150)
Square of initial wealth × 1000	-4.91e-09***	1.08e-08
	(1.56e-09)	(1.02e-08)
Constant	908.8	151.3*
	(604.6)	(78.14)
Observations	269	269
R-squared		0.156
Number of pid	238	238

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

APPENDIX F

PRODUCTIVITY AND RISK EFFECT ESTIMATES

F.1 Marginal Physical Products and Elasticities of Labor and Wealth

The household maize yield function is written as:

$$y_2 = \beta_0 + \beta_1 l_{f1} + \beta_2 l_{f1}^2 + \beta_3 l_{f2} + \beta_4 l_{f2}^2 + \beta_5 l_{f1} \cdot l_{f2} + \beta_6 s_0 + \beta_7 s_1 + \beta_8 W_0 + \beta_9 W_0^2 + \psi H + u$$

Marginal physical product of l_{f1}, l_{f2}, and W_0 can be written as:

$$\frac{\partial y_2}{\partial l_{f1}} = \beta_1 + 2\beta_2 l_{f1} + \beta_5 l_{f2}$$

$$\frac{\partial y_2}{\partial l_{f2}} = \beta_3 + 2\beta_4 l_{f2} + \beta_5 l_{f1}$$

$$\frac{\partial y_2}{\partial W_0} = \beta_8 + 2\beta_9 W_0$$

Elasticities of l_{f1}, l_{f2}, and W_0 can be written as:

$$E_{l_{f1}} = \frac{\partial y_2 \cdot l_{f1}}{\partial l_{f1} \cdot y_2} = \frac{\beta_1 l_{f1} + 2\beta_2 l_{f1}^2 + \beta_5 l_{f1} \cdot l_{f2}}{y_2}$$

$$E_{l_{f2}} = \frac{\partial y_2 \cdot l_{f2}}{\partial l_{f2} \cdot y_2} = \frac{\beta_3 l_{f2} + 2\beta_4 l_{f2}^2 + \beta_5 l_{f1} \cdot l_{f2}}{y_2}$$

$$E_{W_0} = \frac{\partial y_2 \cdot W_0}{\partial W_0 \cdot y_2} = \frac{\beta_8 W_0 + 2\beta_9 W_0^2}{y_2}$$

F.2 Marginal Risk Effect for Selected Variables

The conditional yield variance function is written as:

$$V(y_2) = \alpha_0 + \alpha_1 l_{f1} + \alpha_2 l_{f2} + \alpha_3 l_{f1}^2 + \alpha_4 l_{f2}^2 + \alpha_5 l_{f1} \cdot l_{f2} + \alpha_6 W_0 + \alpha_7 W_0^2 + \alpha_8 s_0 +$$

$$\alpha_9 s_0 + \eta X + \varepsilon$$

Therefore the marginal risk effects of l_{f1}, l_{f2}, and W_0 can be expressed as:

$$\frac{\partial V(y_2)}{\partial l_{f1}} = \alpha_1 + 2\alpha_3 l_{f1} + \alpha_5 l_{f2}$$

$$\frac{\partial V(y_2)}{\partial l_{f2}} = \alpha_2 + 2\alpha_4 l_{f2} + \alpha_5 l_{f1}$$

$$\frac{\partial V(y_2)}{\partial W_0} = \alpha_6 + 2\alpha_7 W_0$$

F.3 Marginal Effect of Labor and Wealth on Labor Allocation

Below are the household ex ante labor allocation decision rules:

$$l_{f1} = \omega_0 + \omega_1 s_0 + \omega_2 W_0 + \omega_3 W_0^2 + \omega_4 \sqrt{V_1} + \omega_5 I_1 + \omega_6 I_1^2 + \eta H + \mu_i^{lf1} + \varepsilon_{it}^{lf1}$$

$$l_{w1} = \tau_0 + \tau_1 s_0 + \tau_2 W_0 + \tau_3 W_0^2 + \tau_4 \sqrt{V_1} + \tau_5 I_1 + \tau_6 I_1^2 + \xi H + \mu_i^{lw1} + \varepsilon_{it}^{lw1}$$

Marginal risk effects of exogenous income and initial wealth on ex ante labor allocation can be expressed as:

$$\frac{\partial l_{f1}}{\partial I_1} = \omega_5 + 2\omega_7 I_1 \qquad \frac{\partial l_{f1}}{\partial W_0} = \omega_2 + 2\omega_3 W_0$$

$$\frac{\partial l_{w1}}{\partial I_1} = \tau_5 + 2\tau_7 I_1 \qquad \frac{\partial l_{w1}}{\partial W_0} = \tau_2 + 2\tau_3 W_0$$

Below are the household ex post labor allocation decision rules:

$$l_{f2} = \gamma_0 + \gamma_1 l + \gamma_2 s_0 + \gamma_3 s_1 + \gamma_4 W_0 + \gamma_5 W_0^2 + \gamma_6 \sqrt{V_2} + \gamma_7 I_1 + \gamma_8 I_2 + \gamma_9 I_1^2 + \gamma_{10} I_2^2 + \chi H + \mu_i^{lf2} + \varepsilon_{it}^{lf2}$$

$$l_{w2} = \psi_0 + \psi_1 l + \psi_2 s_0 + \psi_3 s_1 + \psi_4 W_0 + \psi_5 W_0^2 + \psi_6 \sqrt{V_2} + \psi_7 I_1 + \psi_8 I_2 + \psi_9 I_1^2 + \psi_{10} I_2^2 + \varphi H + \mu_i^{lw2} + \varepsilon_{it}^{lw2}$$

Marginal risk effects of exogenous income and initial wealth on ex post labor allocation can be expressed as:

$$\frac{\partial l_{f2}}{\partial I_1} = \gamma_7 + 2\gamma_9 I_1 \qquad \frac{\partial l_{f2}}{\partial I_2} = \gamma_8 + 2\gamma_{10} I_2 \qquad \frac{\partial l_{f2}}{\partial W_0} = \gamma_4 + 2\gamma_5 W_0$$

$$\frac{\partial l_{w2}}{\partial I_1} = \psi_7 + 2\psi_9 I_1 \qquad \frac{\partial l_{w2}}{\partial I_2} = \psi_8 + 2\psi_{10} I_2 \qquad \frac{\partial l_{w2}}{\partial W_0} = \psi_4 + 2\psi_5 W_0$$

APPENDIX G

TEST OF HYPOTHESES

G.1 Hausman's Specification Test

G.1.1 Comparison of Fixed and Random Effects Estimation of Household Expected Maize Yield in the Planting Period

	Coefficients (b) fixed1	(B) random1	(b-B) Difference	sqrt(diag(V_b-V_B)) S.E.
season1	20.83977	14.34064	6.499133	9.995476
season2	9.316108	1.371225	7.944883	11.5965
daysmiss_p~g	-9.580925	11.16098	-20.74191	9.704839
initwealth	-9.09e-06	.0000147	-.0000238	.0000144
initwealth~q	7.68e-10	-6.71e-10	1.44e-09	1.20e-09

```
                         b = consistent under Ho and Ha; obtained from xtreg
          B = inconsistent under Ha, efficient under Ho; obtained from xtreg

    Test:  Ho:  difference in coefficients not systematic

                  chi2(3) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                          =        6.99
                Prob>chi2 =      0.0721
                (V_b-V_B is not positive definite)
```

G.1.2 Comparison of Fixed and Random Effects Estimation of Household Expected Maize Yield in the Preharvest Period

	Coefficients (b) fixed2	(B) random2	(b-B) Difference	sqrt(diag(V_b-V_B)) S.E.
season1	-15.76359	-11.51404	-4.249552	14.03507
season2	-23.8969	-24.56247	.6655676	14.32875
vals_preha~t	-9.448127	14.00723	-23.45536	50.88531
damage_pre~2	.2456726	-8.216031	8.461704	20.70245
daysmiss_p~g	1.57196	14.80395	-13.23199	10.69736
daysmiss_p~t	-4.205198	4.896981	-9.102179	10.96871
nex_prehar~t	-80.01682	-56.46845	-23.54837	23.51342
initwealth	-2.56e-06	.0000167	-.0000192	.0000155
initwealth~q	4.51e-10	-8.19e-10	1.27e-09	1.19e-09

```
                         b = consistent under Ho and Ha; obtained from xtreg
          B = inconsistent under Ha, efficient under Ho; obtained from xtreg

    Test:  Ho:  difference in coefficients not systematic

                  chi2(7) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                          =       10.14
                Prob>chi2 =      0.1807
```

G.1.3 Comparison of Fixed and Random Effects Estimation of Household Maize Yield Function

	Coefficients (b) fixed	(B) random	(b-B) Difference	sqrt(diag(V_b-V_B)) S.E.
lab_plant	-.0017133	2.139634	-2.141347	1.094443
lab1_sq	.0460269	.0107998	.0352271	.0219045
lab_preharv	-2.03695	2.763157	-4.800107	1.409793
lab2_sq	.0060481	-.0062718	.0123199	.0358767
lab1_2	.0704646	-.0569232	.1273878	.0615201
vals_preha~t	.0324614	-33.35184	33.3843	36.16453
damage_pre~2	5.871413	22.99313	-17.12172	14.32484
daysmiss_p~g	5.896071	11.87595	-5.979879	7.794226
daysmiss_p~t	5.573586	2.254179	3.319407	9.008727
nex_prehar~t	-71.93232	-26.23361	-45.69872	.
season1	-4.383934	-.0286047	-4.355329	15.31922
season2	-12.54446	-13.28607	.7416045	14.60906
initwealth	9.15e-06	.0000185	-9.35e-06	2.74e-06
initwealth~q	-5.08e-10	-8.18e-10	3.11e-10	5.26e-10

```
                b = consistent under Ho and Ha; obtained from xtreg
 B = inconsistent under Ha, efficient under Ho; obtained from xtreg

Test:  Ho:  difference in coefficients not systematic

           chi2(11) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                    =       16.01
          Prob>chi2 =      0.1407
          (V_b-V_B is not positive definite)
```

G.1.4 Comparison of Fixed and Random Effects Estimation of Planting Period On-farm Labor Allocation Model

	Coefficients (b) fixedl1	(B) randoml1	(b-B) Difference	sqrt(diag(V_b-V_B)) S.E.
polim	-50.19986	-28.263	-21.93686	25.69042
polim_sq	31.81159	23.05887	8.752724	21.57333
daysmiss_p~g	-1.170472	.340719	-1.511191	2.695705
sd1	1.605289	-.5488995	2.154189	1.247114
initwealth	-4.09e-06	7.62e-07	-4.85e-06	3.51e-06
initwealth~q	3.31e-10	-2.64e-11	3.57e-10	2.74e-10
farm_inc1	3.33e-06	-1.23e-06	4.56e-06	8.72e-06
farminc1_sq	-2.15e-10	9.95e-11	-3.14e-10	1.32e-09
season1	-3.797646	-9.080425	5.282779	4.746456
season2	8.808049	-9.354348	18.1624	11.52584

```
                b = consistent under Ho and Ha; obtained from xtreg
 B = inconsistent under Ha, efficient under Ho; obtained from xtreg

Test:  Ho:  difference in coefficients not systematic

            chi2(6) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                    =        6.66
          Prob>chi2 =      0.3535
          (V_b-V_B is not positive definite)
```

G.1.5 Comparison of Fixed and Random Effects Estimation of Planting Period Non-farm Labor Allocation Model

	Coefficients (b) fixedn1	(B) randomn1	(b-B) Difference	sqrt(diag(V_b-V_B)) S.E.
polim	3.962128	-33.25744	37.21957	9.574963
polim_sq	-1.11537	28.92366	-30.03903	8.405274
daysmiss_p~g	1.755217	-.3740474	2.129264	.8887908
sd1	1.120465	.6445816	.4758838	.4964482
initwealth	1.84e-07	-7.82e-07	9.66e-07	2.01e-06
initwealth~q	-2.66e-11	1.72e-10	-1.98e-10	1.69e-10
farm_inc1	.0000145	7.36e-06	7.15e-06	5.49e-06
farminc1_sq	-2.12e-09	-9.60e-10	-1.16e-09	8.45e-10
season1	-.1212203	-6.929165	6.807945	2.305515
season2	6.207714	-3.669557	9.877271	4.934131

```
                  b = consistent under Ho and Ha; obtained from xtreg
   B = inconsistent under Ha, efficient under Ho; obtained from xtreg

Test:  Ho:  difference in coefficients not systematic

             chi2(6) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                     =       27.44
           Prob>chi2 =      0.0001
           (V_b-V_B is not positive definite)
```

G.1.6 Comparison of Fixed and Random Effects Estimation of Preharvest Period On-farm Labor Allocation Model

	Coefficients (b) fixedl2	(B) randoml2	(b-B) Difference	sqrt(diag(V_b-V_B)) S.E.
lab_p	-.6078341	1.317695	-1.925529	1.997573
labp_sq	.0195212	-.0102124	.0297336	.0618993
nflab_1	-.8172194	.3540227	-1.171242	2.206546
nflab1_sq	-.154653	-.0000121	-.1546409	.1196277
polim_sq	1.702315	4.830507	-3.128192	10.95021
vals_preha~t	-12.78117	-2.17332	-10.60785	27.60188
damage_pre~2	-8.149845	-1.847538	-6.302306	13.71326
daysmiss_p~g	-4.153856	.8778626	-5.031719	8.50184
daysmiss_p~t	1.503781	-.9649505	2.468731	6.294124
nex_prehar~t	11.8066	-1.660445	13.46704	20.47531
sd2	-.366884	-.2100311	-.1568529	1.289249
season1	-5.357476	5.731146	-11.08862	17.49409
season2	-7.598573	1.997478	-9.596051	13.70529
farm_inc1	.0000343	-8.85e-07	.0000352	.0000289
farm_inc2	.000017	2.05e-06	.000015	.0000659
farminc1_sq	-5.02e-09	1.93e-10	-5.21e-09	4.20e-09
farminc2_sq	-9.29e-11	-1.12e-12	-9.17e-11	1.37e-10
initwealth	1.23e-06	-1.30e-06	2.53e-06	8.27e-06
initwealth~q	-7.75e-11	6.51e-11	-1.43e-10	5.39e-10

```
                  b = consistent under Ho and Ha; obtained from xtreg
   B = inconsistent under Ha, efficient under Ho; obtained from xtreg

Test:  Ho:  difference in coefficients not systematic

            chi2(13) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                     =        8.07
           Prob>chi2 =      0.8390
           (V_b-V_B is not positive definite)
```

G.1.7 Comparison of Fixed and Random Effects Estimation of Preharvest Period Non-farm Labor Allocation Model

	Coefficients (b) fixedn2	(B) randomn2	(b-B) Difference	sqrt(diag(V_b-V_B)) S.E.
lab_p	-2.765991	.2546033	-3.020595	1.332699
labp_sq	.0855704	-.0018371	.0874075	.0413544
nflab_1	-.044825	-.0246797	-.0201453	1.474346
nflab1_sq	-.0245124	.0000545	-.0245669	.0799534
polim_sq	-6.552005	3.129078	-9.681083	5.583058
vals_preha~t	-34.92363	-1.110756	-33.81287	18.38528
damage_pre~2	7.801928	-3.293638	11.09557	9.100529
daysmiss_p~g	-14.67611	1.320934	-15.99704	5.631993
daysmiss_p~t	6.499822	.21489	6.284932	4.151958
nex_prehar~t	-16.17403	-.7800573	-15.39398	13.63079
sd2	1.618487	.0423937	1.576093	.8585381
season1	-20.8547	.3388545	-21.19355	11.62943
season2	-2.569792	10.82439	-13.39419	9.072312
farm_inc1	.0000149	-2.05e-07	.0000152	.0000193
farm_inc2	.0000212	-2.30e-06	.0000235	.000044
farminc1_sq	-1.43e-09	-2.94e-11	-1.40e-09	2.81e-09
farminc2_sq	-2.83e-11	6.98e-13	-2.90e-11	9.19e-11
initwealth	5.64e-06	2.63e-07	5.38e-06	5.52e-06
initwealth~q	-1.09e-10	-2.29e-11	-8.59e-11	3.59e-10

```
                           b = consistent under Ho and Ha; obtained from xtreg
            B = inconsistent under Ha, efficient under Ho; obtained from xtreg

    Test:  Ho:  difference in coefficients not systematic

                 chi2(13) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                          =       13.30
                Prob>chi2 =      0.4248
                (V_b-V_B is not positive definite)
```

G.2 Wald Tests of Significance

G.2.1 Test of Joint Significance of the Effect of Idiosyncratic Shocks on Maize Yield for Random Effects Model

```
 ( 1)  vals_preharvest = 0
 ( 2)  damage_preharvest2 = 0
 ( 3)  daysmiss_planting = 0
 ( 4)  daysmiss_preharvest = 0

           chi2(  4) =    4.68
         Prob > chi2 =    0.3216
```

G.2.2 Test of Joint Significance of the Effect of Initial Wealth Variables on Maize Yield for Random Effects Model

```
 ( 1)  initwealth = 0
 ( 2)  initwealth_sq = 0
       Constraint 2 dropped

           chi2(  1) =    1.73
         Prob > chi2 =    0.1889
```

G.2.3 Test of the Joint Significance of the Effect of Initial Wealth Variables on Planting Period On-farm Labor allocation for Random Effects Model

```
 ( 1)  initwealth = 0
 ( 2)  initwealth_sq = 0
       Constraint 2 dropped

           chi2(  1) =    0.48
         Prob > chi2 =    0.4886
```

G.2.4 Test of the Joint Significance of the Effect of Initial Wealth Variables on Planting Period Non-farm Labor allocation for Random Effects Model

```
 ( 1)  initwealth = 0
 ( 2)  initwealth_sq = 0
       Constraint 2 dropped

       F(  1,   236) =    0.01
            Prob > F =    0.9404
```

G.2.5 Test of Joint Significance of Effect of Planting Period On-farm Labor Allocation on Preharvest Period On-farm Labor Allocation for Random Effects Model

```
 ( 1)  lab_p = 0
 ( 2)  labp_sq = 0

           chi2(  2) =   31.00
         Prob > chi2 =    0.0000
```

G.2.6 Test of the Joint Significance of the Effect of Planting Period Non-farm Labor Allocation on Preharvest Period On-farm Labor Allocation for Random Effects Model

```
( 1)  nflab_1 = 0
( 2)  nflab1_sq = 0

          chi2(  2) =  869.58
        Prob > chi2 =    0.0000
```

G.2.7 Test of the Joint Significance of the Effect of Idiosyncratic Shocks on Preharvest Period On-farm Labor Allocation for Random Effects Model

```
( 1)  vals_preharvest = 0
( 2)  damage_preharvest2 = 0
( 3)  daysmiss_planting = 0
( 4)  daysmiss_preharvest = 0
( 5)  nex_preharvest = 0

          chi2(  5) =    1.33
        Prob > chi2 =    0.9315
```

G.2.8 Test of the Joint Significance of the Effect of Initial Wealth Variables on Preharvest Period On-farm Labor Allocation for Random Effects Model

```
( 1)  initwealth = 0
( 2)  initwealth_sq = 0
      Constraint 2 dropped

          chi2(  1) =    3.07
        Prob > chi2 =    0.0796
```

G.2.9 Test of the Joint Significance of the Effect of Planting Period On-farm Labor Allocation on Preharvest Period Non-farm Labor Allocation for Random Effects Model

```
( 1)  lab_p = 0
( 2)  labp_sq = 0

          chi2(  2) =    2.03
        Prob > chi2 =    0.3633
```

G.2.10 Test of the Joint Significance of the Effect of Planting Period Non-farm Labor Allocation on Preharvest Period Non-farm Labor Allocation for Random Effects Model

```
 ( 1)  nflab_1 = 0
 ( 2)  nflab1_sq = 0

           chi2(  2) =    1.10
         Prob > chi2 =    0.5757
```

G.2.11 Test of the Joint Significance of the Effect of Idiosyncratic Shocks on Preharvest Period Non-farm Labor Allocation for Random Effects Model

```
 ( 1)  vals_preharvest = 0
 ( 2)  damage_preharvest2 = 0
 ( 3)  daysmiss_planting = 0
 ( 4)  daysmiss_preharvest = 0
 ( 5)  nex_preharvest = 0

           chi2(  5) =    4.00
         Prob > chi2 =    0.5490
```

G.2.12 Test of the Joint Significance of the Effect of Initial Wealth Variables on Preharvest Period Non-farm Labor Allocation for Random Effects Model

```
 ( 1)  initwealth = 0
 ( 2)  initwealth_sq = 0
       Constraint 2 dropped

           chi2(  1) =    0.55
         Prob > chi2 =    0.4598
```

G.2.13 Test of the Joint Significance of the Effect of Idiosyncratic Shocks on Yield Risk for White Correction

```
 ( 1)  vals_preharvest = 0
 ( 2)  damage_preharvest2 = 0
 ( 3)  daysmiss_planting = 0
 ( 4)  daysmiss_preharvest = 0
 ( 5)  nex_preharvest = 0

       F(  5,   247) =    0.57
            Prob > F =    0.7196
```

G.2.14 Test of the Joint Significance of the Effect of Idiosyncratic Shocks on Yield Risk for Iterative Correction

```
 ( 1)  vals_preharvest = 0
 ( 2)  damage_preharvest2 = 0
 ( 3)  daysmiss_planting = 0
 ( 4)  daysmiss_preharvest = 0
 ( 5)  nex_preharvest = 0

       F(  5,   247) =    0.91
            Prob > F =    0.4724
```

G.3 Breusch-Pagan's Test of Heteroscedasticity

Conditional Yield Variance Function

```
chi2(21)      =   733.07
Prob > chi2   =   0.0000
```

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